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Impact Of Social Media On Public Perception Of Government Covid-19 Response Efforts

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IMPACT OF SOCIAL MEDIA ON PUBLIC PERCEPTION OF GOVERNMENT COVID-19 RESPONSE EFFORTS

A Thesis Submitted by

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ABSTRACT

In Egypt, there was negative feedback over the lower-than-expected COVID-19 cases reported by the Ministry of Health and Population. This feedback came from speculation that the cases or deaths were higher than reported. The publications lead to an unwarranted overall negative perception of government efforts to contain or respond to the pandemic. *Saied AA, Metwally AA, Madkhali NAB, Haque S and Dhama K (2021)*

This research aims to understand this phenomenon to provide insights into how governments can perform better in times of crisis regarding social media and its impact on public opinion. This research aims to understand how social media impacts public perception of government COVID-19 response efforts by studying Facebook comments, likes, and reactions (emoticons).

The study was based on data gathered from Facebook comments on the daily infographic COVID-19 statistics from the official site of the Ministry of Health and Population. The sampling frame is the 52 weeks of 2020, January to December, through random sampling resulting in 546 comments. The comments were analyzed for items including likes, reactions, time of entry, and collection. The data items were analyzed by an AI algorithm and assigned a positive or negative rating (auto-sentiment) which is a byproduct of the sentiment detected and the degree of certainty of that detection. The multiple regression model used to test the two hypotheses showed that both were supported. The study found that the more negative or positive the comment is, the more the number of replies and reactions it receives.

Lastly, a two-step model is suggested to help policymakers address the issue in the future. This policy aims to mitigate the confusion, and semi-regulate online civil discourse. Additionally, analysis of alternative solutions' inefficiency is displayed to help strengthen the proposed model's logos.

CHAPTER 1: INTRODUCTION

Covid-19 has been the main headline worldwide for the past two years since it was declared a global pandemic (Cucinotta 2020). Given that in this day and age, the whole world is connected through social media, information about the pandemic was virally being propagated. Information and disinformation ranged from topics like how deadly this pandemic is to medication speculations; all were widely available to the public to delude it further. As a result, there was mass panic and mental health decline due to rising stress from the quarantines and paranoia from illness (Bagus 2021).

A global call for action for a mass quarantine, like COVID-19, has been unprecedented since the early 2000s. In 2003 many countries worldwide went into lockdown for the SARS virus outbreak. Historically, quarantine is a part of how the world fights the viral spread of infectious diseases. To control the spread of SARS, there was a 3-month extended quarantine globally. SARS has caused just over 100 million infections. (Feehan, pp. 56) It was reported in Toronto that the quarantine for SARS has been ineffective and insufficient in dealing with it. In Toronto, excessive quarantining proved highly costly as a strategy when juxtaposed with the more effective combat efforts in Beijing. In Beijing, they quarantined 12 potentially infected people for every single infected person with SARS, compared to Toronto, where up to 100 encountered cases were quarantined for each single detected case. (Schabas, 2004) Studies suggest that Canada quarantined at least an extra 25 people that didn't need it. Also, when it came to enforcing quarantine, Toronto officials could not successfully enforce a full quarantine; only 57% followed the actual quarantine rules and were compliant. This dissonance left politicians and doctors alike puzzled about how quarantining will work when a sizable portion of the public doesn’t follow the preventive guidelines needed to achieve improvements in the combat for the eradication of the pandemic. SARS and the history of its transmission have been documented thoroughly since 2003. Indeed, the evidence shown by recent studies about SARS is compelling. (Schabas, 204)

H1N1, or “swine flu,” first appeared in America in April 2010 (Bhadoria et al., 2021). The swine flu spreads the same way the seasonal flu does from one person to another through contact or even touching an infected surface. Like the flu, if you get the swine flu, it is unlikely you could get it again. The illness varied from one person to another, from mild to severe (Bhadoria et al., 2021). The severity depends on if a person is high-risk or low-risk and the preexisting condition of a person's health. Most studies about infectious diseases show that to combat these kinds of illnesses, you must seek treatment and quarantine as soon as the illness is contracted (Bhadoria et al., 2021).

Whenever a quarantine is enforced, it causes controversy; the public is polarized into those who support the decisions and others that do not. (Tongotti, 2013) Some see it as a lack of freedom and unethical. Others question whether quarantine is effective enough to be worth its negative consequences, and this is why the public health authorities should uphold transparency and honesty. (Upshur, 2003) The lockdown affects many of the public economically, mentally, and emotionally. Due to covid-19, people lost their jobs and had to close businesses. Moreover, routines were disrupted, especially those of children and parents. Emotionally, people suffer from separation anxiety from their loved ones and fear of infectious diseases. Additionally, cases of suicide have been reported to increase during COVID-19 and quarantine. (Embaby et al., 2021)

The first known quarantine occurred during the black plague, which rampaged Europe from 1347-1352, leading to the first organized institutional measures of disease control to be implemented. When the plague first arrived in Sicily from the eastern Mediterranean, it quickly spread throughout Europe, causing a massive amount of fatalities estimated to be 30% of the world’s population at the time. (Tongotti 2013) (Feehan, 2021)

In the last two decades, epidemics spread and alarmed entire regions, such as the AIDS virus, Ebola, H1N1 influenza, the swine flu, and Zika virus, to name a few. (Gupta and Sahu, 2021) However, none have had the scale of COVID-19 since the black plague, also known as the bubonic plague. COVID-19 is primarily a concern due to the speed of its spread. (Feehan, 2021) As of February 2021, COVID-19 has caused 2.1 million deaths globally (2%-4% fatality rate), which is not as fatal as the bubonic plague, which had a fatality rate of 30-60%. (Feehan, 2021)

Another distinction of COVID-19 was the role social media played in spreading rumors and misinformation, instigating mass-panic. (Dubey et al., 2020) Where in other pandemics, the media was limited and organized by 2019, social media has developed into an unlimited, instant, unpredictable sphere of free expression in which a cornucopia of truths is available. Social Media’s role in creating mass panic during COVID-19. COVID-19 spread suddenly and rapidly and had no known cure, which naturally caused anxiety and fear, which led to mass panic. Due to the unforeseen chaos that transpired, mass panic management became essential during this epidemic. Ahmad, A. R., & Murad, H. R. (2020)

Social media has played a critical role in shaping public perception of governments' Covid-19 response efforts worldwide. With the rapid spread of Covid-19 and the associated uncertainty, social media has become the primary source of information for many people, and governments have had to adapt their communication strategies to address this new reality. This thesis examines the impact of social media on public perception of governments' Covid-19 response efforts worldwide and reviews best practice cases. Basch, C. H., Basch, C. E., Hillyer, G. C., & Meleo-Erwin, Z. C. (2022).

1.1 Social Media and Public Perception

Social media platforms such as Twitter, Facebook, Instagram, and YouTube have become ubiquitous in people's lives and have transformed the way information is shared and consumed. In the context of Covid-19, social media has played a vital role in shaping public perception of the disease and the government's response efforts. (Kim & Zhong, 2021)Social media has enabled governments to communicate with the public more quickly and efficiently, but it has also given rise to misinformation, conspiracy theories, and fake news, which have had a significant impact on public perception (Rovetta & Bhagavathula, 2020).

A study by Pew Research Center (2020a) found that social media is the most common source of news among Americans, with 55% of adults saying they get news from social media often or sometimes. This trend is even more pronounced among younger generations, with 71% of 18- to 29-year-olds saying they get news from social media. This means that social media is an important tool for governments to communicate with the public about Covid-19 and their response efforts (Meyer, Gericke, & Sirois, 2020).

However, Pew Researh Center (2020b) found that social media is a significant source of misinformation, with 62% of Americans saying they have seen fake news about Covid-19 on social media. This misinformation can have a profound impact on public perception and can undermine the government's response efforts. For example, a study by the Reuters Institute (2020) found that people who believe in Covid-19 conspiracy theories are less likely to follow government guidelines and more likely to engage in risky behaviors such as attending large gatherings.(Mitchel, Leideka,2021)

The Covid-19 pandemic has had a significant impact on the world, and Egypt was not exempt from this impact. The Egyptian government has been criticized for its handling of the pandemic, and social media played a significant role in highlighting the concerns of citizens. In this review, we will examine the Egyptian government's response to the pandemic and how it was received on social media. (OECD, 2020)

The Egyptian government's response to the Covid-19 pandemic was initially slow. In March 2020, the government closed schools and universities, suspended flights, and implemented a curfew. However, many people criticized the government's response, with some saying that the measures were too little, too late. Furthermore, many people complained that the government was not doing enough to protect its citizens, especially those who were most vulnerable to the virus (Elsamadouny, 2020).

The government's communication with the public was also a point of concern. Some people felt that the government was not transparent enough in its communication, and that it was not providing accurate information about the situation. Furthermore, some people believed that the government was downplaying the severity of the situation, which led to people being less cautious and more likely to contract the virus (Hegazy, Zaki, Salem, & Salem, 2020).

Social media played a significant role in highlighting these concerns. Twitter and Facebook were the primary platforms used to criticize the government's response to the pandemic. Many people took to these platforms to express their frustration and anger, with some calling for the government to take more drastic measures to combat the virus. Furthermore, social media was also used to share information about the virus and to raise awareness about the importance of social distancing and wearing masks (Megahed, 2021).

However, the government was not entirely unresponsive to the criticism it received on social media. The Ministry of Health and Population created a Facebook page to provide citizens with accurate information about the virus, and it also used social media to raise awareness about the importance of following safety measures (Salahuddin, Hossain, & Khalil, 2020).

There were negative feedback over the lower-than-expected COVID-19 case reported by the Ministry of Health and Population in Egypt. This feedback came from speculation that the cases or deaths were higher than reported, as well as an announcement that Egypt was aiding Italy and the United States with medical supplies that were rumored to be in shortage locally (Mandour 2020). The publications lead to an unwarranted negative perception of government efforts to contain or respond to the pandemic. (Mandour 2020).

In conclusion, the Egyptian government's response to the Covid-19 pandemic was initially slow, and it was criticized by many people. Social media played a significant role in highlighting these concerns and in spreading information about the virus. However, the government did take some steps to respond to the criticism it received on social media, and it used social media to communicate with the public. Nonetheless, it is essential for the government to take the criticism seriously and to address the concerns of citizens to better handle future crises.

Social media has played a crucial role in shaping public perception of governments' Covid-19 response efforts worldwide. It has become an essential tool for people to access news, share information, and communicate with others. Social media platforms such as Twitter, Facebook, and Instagram have allowed people to voice their opinions and share their experiences during the pandemic. Social media has become a vital source of information for people worldwide, and it has helped to shape public opinion on how governments have responded to the pandemic.(Al-Dmour, H., Masa'deh, R., Salman, A., Abuhashesh, M., & Al-Dmour, R. ,2020)

Social media has also played a significant role in shaping public opinion on government responses to the pandemic. Social media has allowed people to share their experiences with lockdowns, mandatory masks, and other measures implemented by governments. Social media platforms have been used to criticize government responses to the pandemic, with users sharing images and videos of crowded hospitals, long queues for testing, and other issues. Social media has also been used to highlight successful government responses to the pandemic, with users sharing positive experiences and news articles about government responses. Media Effects (Theory Cascini, F., Pantovic, A., Al-Ajlouni, Y. A., Failla, G., Puleo, V., Melnyk, A., Lontano, A., & Ricciardi, W. ,2022)

This research aims to determine how social media impact public perception of government response efforts to COVID-19. Specifically, the study examines how social media impacts the reception and perception of the public when it comes to news officiated by the Egyptian government.

1.1 Statement of the Problem

While it is well documented that social media distorts the users' perception of reality, its qualities as a platform for government to public communication are less explored. Moreover, social media as an environment for government to public communication during times of crisis is even less researched. The inability to predict what happens on social media when paired with government communication poses a threat to national security, especially in times of crisis. With scientists predicting more epidemics, a proper understanding of social media reactionary trends needs to be enhanced to deal with the threats of chaos, anarchy, and propaganda. (Marani, 2021) Not being able to understand social media's applications has led to massive problems, such as the mass recruitment of susceptible people to ISIS, and the Russian meddling in the 2016 US elections, to name a few. (Benkler, 2018) Therefore, it is crucial to move forward with speed in the race against expanding this realm of civic-public discourse.

This research aims to inform and give insight into the tendencies and trends of reactionary tools on social media, specifically the largest and most inclusive platform

(Facebook), and their impact on public perception of government performance in times of crisis. The research focuses on the Egyptian government during the COVID-19 pandemic as a case study. More case studies from different regions of the world need to be researched using the same model to corroborate the inferential findings from this research. Further validation is required because different regimes have different relationships and histories with different populations. Perhaps, the results found in a developed nation are different from developing nation (Song & Meier, 2018).

Furthermore, results may also vary depending on the governance type of the researched nation. The world's governments and peoples are not all the same, and governments can be autocratic, communist, or democratic and certainly don't all follow the same degrees of enforcement. Additionally, populations vary from education, health, and wealth to male hegemony, age, ethnicity, and religion demographics. These differences make it inaccurate to assume results from one case study can apply to all. Scheppele, K. L. (2018)

The relevance of this direction in research stems from the speed of social media as a paralyzing force against public policy. Today, lawmakers cannot stay ahead of social media growth as its exponential growth has reached a point where it grows and morphs faster than laws can be created and ratified anywhere in the world. This power gap keeps growing with the reach of social media platforms to more and more people globally. In the eyes of many, social media platforms like Facebook are often perceived as more potent than their local governments because they cannot be censored. Some can perceive Facebook as having hegemony over the local government. In 2017, a study concluded that Facebook's revenues in 2017 were more than 105 countries' total GDP for that year. (Belinchón, 2018) Statistics, like the former, influence the public's perception of the power of these platforms when that perception of power turns into trust and credibility.

To prevent this association from creating mass distrust in the government, this research focuses on the comments section, the ecosystem in which social media discussions flourish. This research aims to quantify the reactions, comments, and replies on the official Facebook MOHP page and analyze the discussion to depict how public perception is formed on the platform accurately.

CHAPTER 2: LITERATURE REVIEW

2.2 Social Media Measurements

Many studies dealing with public opinion readings on social media platforms use sentiment reading tools to quantify the data collected from social media. In a research titled “Climate Change Sentiment on Twitter: An Unsolicited Public Opinion Poll”, Cody et al. (2015) try to measure public opinion on climate change through the social media Twitter lense. Auto-sentiment readings were used to determine public opinion on climate change. In the research, the auto-sentiment measurement tool is called the “Hednometer”. Essentially, the purpose of this tool is to measure how public opinion on Twitter changes with different climate change events, news, and natural disasters (Cody et al. 2015).

Cody et al.’s study found a correlation between how public sentiment, referred to as “happiness,” is positively affected by certain pro-climate change events like climate change rallies, green ideas contests, book releases, etc. Conversely, events like disasters, oil drilling, and climate bills negatively affected sentiment, making public opinion on social media read (Stark, 2020).

Information has to be harvested from the post to use an auto-sentiment tool on social media posts done through script-coded algorithms that can extract the numbers and texts from social readings, such as likes/dislikes, reactions, reposts, comments, etc. According to El Baradei et al. (2021), there is even a script-coded social data mining tool called "CrowdTangle" that Facebook offers data for academics wanting to harvest data from their platform. Algorithmic data mining tools are usually the most used in social media-related studies, whereby data sets are extracted from social media platforms.

2.3 Public opinion and Government Performance

It is generally agreed that social media has become the central platform for the general public to obtain information and express themselves (Han et al., 2020). This open forum has caught world leaders and governments by storm. Social media sites such as Facebook or Twitter play a pivotal role in politics (Klašnja et al., 2015), which alarmed governments since social media has become the primary source of news and information, particularly breaking news events. Additionally, traditional media has incorporated feedback mechanisms from their viewers through social media. Moreover, even political actors have come to rely more on social media than press releases to reach the public (Jungherr et al., 2020).

Ironically, the public and government feel strongly about social media because it holds policymakers more accountable and responsive to the people. However, the reality that neither can deny is the potential that social media brings to considerably reduce the time and cost of monitoring public opinion (Zhuravskaya et al., 2020). In other words, governments pay attention to public opinion because, in a true democracy, the public wields the trustworthy source of power, not the government (Oldendick 2002). Oldendick also states that a public official's job is to do what the public wants. Therefore, it is their job to determine what the public wants, i.e., public opinion. Therefore, we conclude that public opinion is used to determine government performance and the compass for government sectors to find their direction. This cycle and how well it functions impact the progress or decline of states to maintain political stability (Hur, 2018).

After seeing how effective social media platforms like Twitter were in politics when utilized by ex-president Obama in the 2008 US Elections and the Arab Spring, many state actors and government entities/organizations adopted official social media accounts (Mishaal & Abu-Shanab, 2015). These accounts are now used to keep the populace updated with official announcements, statements, and updates.

The presence of an e-government model's success can be measured in the following: transparency, participation, collaboration, comfort, and posted topics in the communication between citizens and governments (Mishaal & Abu-Shanab, 2015). In some examples, the social media accounts used by governments are utilized as a one-way method of communication and not designed for two-way communication (Linders, 2021), such as in our case study of Egypt (Abdelsalam et al., 2013). On the other hand, in the other examples, e-government social media accounts are designed and employed to facilitate more discussion and interactive feedback loops (Ruess et al., 2021).

The Covid-19 pandemic has changed how we live, and the role of mass media and social media in this crisis cannot be underestimated. (Hussain, 2020) Social media can be used to help individuals to adhere to safety measures and promote positive health attitudes. However, it can also be a source of misinformation and discrimination. (Hussain, 2020) Governments can use mass media to discourage people from spreading false information. In contrast, public health personnel, teachers, and religious and political leaders should also use social media to provide accurate and informative updates. (Hussain, 2020)

2.5 Egypt and Social Media

Social media had a significant influence in Egypt post the Arab Spring revolutions in 2011, and it has become essential for the global mobilization, planning, and execution of social movements. Although it is inaccurate to give the credit of a revolution to one social media platform, social media undoubtedly collectively increased the populace's desire for a better future, democracy, and economical and political growth that had been halted for many years by successive administrations (Kamel, 2014a). Furthermore, it is fair to say that social media was at the epicenter of the protests, serving as a critically impactful aid in organizing and mobilizing the revolts (Eltantawy & Wiest, 2011). Kamel (2014b) notes that Egypt's government has consistently worked to promote, spread, and institutionalize Information and Communication Technologies (ICT) since the mid-1980s. These efforts have contributed to the significant mobile access to social media amongst Egyptians via laptops, tablets, and mobile phones. Consequently, by 2011 the majority of the public owned was registered to at least one social media platform via an online account (dormant or active). It is crucial to remember that the events of January 2011 were partially the impetus of exponential growth in the use of ICT in recent years, despite the various difficulties and pressures it has experienced (Kamel, 2014b).

Undoubtedly, ICT facilitated activism by allowing the masses a new way to connect and enabling more significant propagation and visibility for their discussions. Remarkably, the aid was helpful for the younger generation, who were more IT literate and looking for a platform to communicate, express their views, and address the issues affecting their future. Most activists chart the revolution's success to social media, citing that it would have taken considerably longer to accomplish if it had not been for the utility of ICT. Social media aided in accelerating both the organization of the many initiatives and the mobilization of people. In other words, limitations on the freedom of speech in public would have stifled the spread of the cause had it not been for ICT. (Kamel, 2014a) The 2011 uprising was one of the first times the Egyptian population and the world got their news live from social media. It is no surprise that social media remained integral to social communication and live news coverage locally and across borders after the uprising. (Kamel, 2014b)

While there is less research on Egypt’s governmental use of social media, Abdelsalam (2013) reported a growth in social media use by the government post-2011 using analytics of all registered governmental websites and social media accounts. (El Baradei et al., 2021) After social media coordinated the Arab Spring revolution in January 2011, all government entities created social media accounts to announce updates and news to the public. However, it is noted that, unlike some western governments, the Egyptian government’s accounts are only meant for announcements and not discussion or feedback (Abdelsalam et al., 2013). In this sense, it is debatable that the Egyptian Government was forced into online participation rather than volunteering to lead a transparent inclusion-targeted communication policy. During the pandemic, the number of Facebook users in Egypt rose, according to NapolenCat statistics; there were 43 million FB users in Egypt in March 2020. The user base grew to 47 million in August 2020 (Baradei et al., 2021; NapoleonCat, 2020).

In Egypt, many changes have occurred since the Arab Spring in the news media landscape. The government installation of fiber optic cables led to the introduction of 4G internet connectivity, which increased the number of users on social media exponentially in Egypt. (Allam and Hollifield, 2021). According to a CAPMAS census in 2019, nearly half of Egypt qualified as mobile internet users, causing internet penetration to reach 50%, while mobile penetration is at 110%. (Allam and Hollifield, 2021) After the revolution, new laws that were less rigid helped create more platforms supporting different political ideologies. Although the law was criticized for not fully supporting freedom of speech, the rise in new news outlets was a reflection. More people relied on getting their news online, instantly, rather than from national outlets (Allam and Hollifield, 2021).

In Egypt, social media news consumption has grown since the coverage of the uprisings from 2011 onward. The coverage led to the national media losing the trust of the Egyptian public for sticking to the protocol and hiding anything damaging to it (Allam 2019). On the other hand, private owned media focused only on attention-grabbing negative stories to attract as much of the public as possible. After the Arab Spring, the media landscape was in a vague transitional system, adjusting to the new status-quo Egyptian power politics (Allam, 2019).

Because freedom of speech is sometimes illusory in the Arab world, media stations are inclined to be pro-government and aid in maintaining the reigning government. Before the Arab spring, the media was notoriously under the government’s control. Even the private media was controlled. (Allam, 2019) Moreover, a huge increase in private media platforms and online websites and social media feeds became developed; everyone could get news on the spot. Although many platforms are privately owned, some laws make it possible for large corporations to spread their ideologies to the public. However, some co-dependency also stemmed from private media outlets depending on government subsidies as an extension of the new laws. (Allam, 2019) Consequently, Egyptian media lost the trust of the Egyptian public, especially politically and economically, and this is where social media became more trusted than state and private media. Studies show that constant negative news can cause desensitization and disengagement. (Allam, 2019)

2.6 Public Opinion in Times of Crisis

Since the last decade, social media platforms have facilitated a broader admittance of public reaction in response to times of crisis (Goodchild, 2011). These reactions have become a public threat since many find a misinformed public opinion on social media can be irrational, infective, and confirmatory (Han et al., 2020). While studies show the positives of social media as a vehicle of public opinion due to its high reach and low cost (Zhuravskaya et al., 2020), social media can cause the public to be impressionable in times of crisis. Public opinion's distribution changes from area to area according to population density, leading to widespread oversaturation of views in cities and other highly populated areas (Han et al., 2020), which can lead to cities imposing on the rural areas and the rural areas not being represented in census readings.

2.6.1 Government Communication Strategies on Social Media

Misinformation about the Covid-19 pandemic has spread rapidly through social media platforms. False information, such as conspiracy theories about the virus's origins or claims that the virus is a hoax, has spread rapidly and has caused confusion and panic among the public. Social media platforms have attempted to combat this misinformation by flagging false information and promoting accurate information. However, the spread of misinformation remains a significant challenge (Cuan-Baltazar et al. 2020).

Studies suggest that fear, anxiety, and depression are highly related to infectious diseases' spread. (Faisal, Shatri, Putranto PP. 179) Like the stigma of Ebola, Covid-19 created even more panic and fear because of the overwhelming social media presence during lockdowns resulting in rumors spurred from inaccurate sources on social media. In addition, the quarantine for COVID-19 included non-infected people working from home, children going to school online, and even exercising at home. Those factions of society that previously had no concerns about fatal illnesses, unlike the elderly, saw high levels of stress and no outlet to do anything about it. This suppression is liable to lead to a state of irrational panic, which distorts the mind's perception of reality, causing a change in human behavior. (Embaby et al., 2021)

Given the importance of social media in shaping public perception of Covid-19 and the government's response efforts, governments worldwide have had to adapt their communication strategies to address this new reality. This section reviews some best practice and worst practice cases of government communication strategies on social media.

Case 1: New Zealand

New Zealand's response to Covid-19 has been widely praised, and the government's communication strategy on social media has played a significant role in this success. The government's social media channels, including the Prime Minister's Facebook page, were used to communicate directly with the public, providing regular updates on the situation and the government's response efforts. The government's communication strategy was characterized by transparency, honesty, and empathy, which helped build trust with the public (New Zealand Government, n.d.).

One example of the government's effective use of social media was a video posted by the Prime Minister, Jacinda Ardern, in which she outlined the government's response to Covid-19 and the importance of staying at home. The video was widely shared and helped to reinforce the government's message to the public (Ardern, 2020, March 21).

Case 2: South Korea

South Korea's response to Covid-19 has also been widely praised, and the government's communication strategy on social media has played a significant role in this success. The government's social media channels, including the Ministry of Health and Welfare's Twitter account, were used to communicate directly with the public, providing regular updates on the situation and the government's response efforts. The government's communication strategy was characterized by transparency, honesty, and data-driven decision-making, which helped build trust with the public (South Korea Ministry of Health and Welfare, n.d.).

One example of the government's effective use of social media was the development of a Covid-19 tracking app that allowed people to check the number of cases in their local area. The app was widely downloaded and helped to keep people informed about the situation (Park & Park, 2020)

While some governments have been praised for their handling of the Covid-19 pandemic, others have been criticized for their responses. In this section, we will review some of the worst cases of governments' handling of the pandemic and the response of the people on social media (Kim & Zhong, 2021).

Case 3. United States

The United States has been widely criticized for its handling of the Covid-19 pandemic. The government's response to the pandemic has been inconsistent, with different states implementing different measures. The federal government's messaging on the pandemic has been confusing, with contradictory statements from different officials. This inconsistency has led to confusion among the public, and the government's response to the pandemic has been widely criticized on social media platforms. (Galaitsi, S. E., Cegan, J. C., Volk, K., Joyner, M., Trump, B. D., & Linkov, I. ,2021)

The US government's response to the pandemic has been politicized, with some politicians downplaying the severity of the virus and promoting unproven treatments. This politicization has led to skepticism among the public about the severity of the virus and the effectiveness of measures to control its spread. Social media platforms have been used to spread misinformation about the virus, with conspiracy theories and false information about the virus's origins spreading rapidly (Meyer, Gericke, & Sirois, 2020).

Case 4. India

India has also been criticized for its handling of the Covid-19 pandemic. The government initially imposed a strict lockdown to control the spread of the virus. However, the lockdown was lifted prematurely, leading to a rapid increase in the number of cases. The government's response to the pandemic has been criticized for being slow and ineffective, with inadequate testing and contact tracing. (Ghosh,2020)

The Indian government's response to the pandemic has been criticized on social media platforms, with users sharing images and videos of overcrowded hospitals and long queues for testing. Social media platforms have been used to criticize the government's response to the pandemic and to highlight the challenges faced by healthcare workers and the public (Bhattacharya, & Banerjee, 2021).

Case 5. Brazil

Brazil has also been criticized for its handling of the Covid-19 pandemic. The government has downplayed the severity of the virus, with the president dismissing it as a "little flu." The government's response to the pandemic has been criticized for being slow and ineffective, with inadequate testing and contact tracing. The government has also been criticized for prioritizing the economy over public health (Vicentini, & De Camargo, 2020).

Social media platforms have been used to criticize the Brazilian government's response to the pandemic, with users sharing images and videos of overcrowded hospitals and long queues for testing. Social media platforms have also been used to highlight the challenges faced by healthcare workers and the public (Chandrasekharan, & Wu, 2021).

Social media has played a significant role in shaping public perception of governments' Covid-19 response efforts worldwide. It has become an essential tool for people to access news, share information, and communicate with others. Social media has allowed people to voice their opinions and share their experiences during the pandemic, and it has helped to shape public opinion on how governments have responded to the pandemic. (Cascini, F., Pantovic, A., Al-Ajlouni, Y. A., Failla, G., Puleo, V., Melnyk, A., Lontano, A., & Ricciardi, W. ,2022)

Some governments have been praised for their handling of the pandemic, with successful measures implemented to control the spread of the virus. However, other governments have been criticized for their responses, with inadequate measures and a slow response to the pandemic (Abbas, Procter, van Zandvoort, & Clark, 2020). Social media platforms have been used to criticize government responses to the pandemic, with users sharing images and videos of crowded hospitals, long queues for testing, and other issues (Rovetta, & Bhagavathula, 2020).

Social media has also been used to highlight successful government responses to the pandemic, with users sharing positive experiences and news articles about government responses. The impact of social media on public perception of governments' Covid-19 response efforts worldwide is significant, and it is essential that governments communicate effectively with the public and use social media platforms to disseminate accurate information (Lwin et al. 2020).

2.7 Social Media during the Pandemic

In the research, Kamar (2021), who studied social media and its panic during the pandemic, was relied on for background context. She focused her research on India but related it to everywhere else. She believes the government should control the information spread on social media and be fact-checked. According to her article, there should be more public awareness and clarity about where to get factual information. She writes about the rise in suicide rates and the decline in mental health and how this is directly related to the negativity on social media. She also discussed vaccinations, how social media spread more anti-vaccination information, and the result. Although we agree with the article about the negative impact of social media during the pandemic, we also believe that even with the official government release of facts, people are more inclined toward adverse reactions on social media (Shehata & Abdeldaim, 2021).

The processing and evaluation of news content on social media reflect how current news is often spread via social media (Boot, Dijkstra, & Zwaan, 2021). This article showed the prevalence of negativity bias, and negative information induces more substantial psychological effects than neutral and positive information. The processing and evaluation of online news content can be influenced by 'likes' and peer 'user comments'. Most results showed that mixed combinations of positive and negative comments considerably affected the reader's personal opinion (Boot, Dijkstra, & Zwaan, 2021). Social media-induced more negative attitudes lowered intent on sharing, reduced agreeability with a specific topic, lowered perceived attitude, and decreased content credibility.

Since news is shared daily on social media, the public is highly influenced by what they read, including peer-shared comments, which are highly related to the bandwagon effect and negative bias (Howard, 2019). Another critical factor is the content type, which varies in ideological congruency. Boot, Dijkstra, & Zwaan (2021) articulated that there are three types of content; ideologically congruent, ideologically incongruent , and ideologically neutral. A custom website using a similar interface to Facebook was designed to navigate the effect of peer-user comments and likes on social media. The site contained new articles highlighting five key features. Presence and omission of likes were added equally to articles, and comments were subjective. Four types of comments existed; favorable, unfavorable, mixed, and no comments. Three types of articles vary in congruency: the first one was congruent and was about climate change and discussed a meeting between Justin Trudeau and Greta Thunberg. The second was an ideologically incongruent article reporting the relationship between violent video games and aggressive behavior. The final one was a weather report, which is considered neutral.

This experiment was preregistered alongside their hypothesis, study design, sample size, analysis type, exclusion criteria, and statistical inference criteria. A sample of 560 participants was chosen, first- and second-year Bachelor of Psychology students, and only 412 were considered. (330 of them females.) There were five main outcome variables: attitude, share intent, ideological congruence (i.e., level of agreement with the content), perceived public attitude, and credibility. (Boot, Dijkstra, & Zwaan, 2021). The main empirical results: There was a significant difference between positive and mixed comments. There is a significant difference between positive and negative comments. Negative and mixed comments resulted in more negative attitudes. Without comments, participants were more positive toward the congruent article and negative toward neutral. A significant effect was found regarding content type—no evidence of likes affecting the participants. The writers concluded that negative comments are more effective due to authority bias. People who leave negative comments are viewed as more intellectual (Boot, Dijkstra, & Zwaan, 2021).

This study is essential to the current research study because both take on the same topic, focusing on social media's relationship with negative bias. We agree that negative comments have a considerable effect generally on the public. Also, both papers focus their research on Facebook comments and likes. On the other hand, what we don't have in common with the paper is the data. We are using actual data collected from Facebook, and the comments are spontaneous, whereas Boot et al.'s research set up an experiment to emulate Facebook. In the research, the participants in the experiment were only psychology undergrads, while this research is more representative because it randomly samples the entire population.

2.7.1 The Role of Social Media during COVID-19

Misinformation about Covid-19 can cause panic and lead to conspiracy theories about bioweapons being used by certain countries, as witnessed during the COVID-19 pandemic, where some speculated that the pandemic is a Chinese bio-weapons. In developing countries such as Pakistan, this can be amplified due to the lack of timely, accurate information from official sources. (Hussain, 2020) Social media can also spread fake remedies, such as herbal products and drinks. (Naeem, 2021)

To combat misinformation, governments should advertise through mass media to remind people not to post anything that minimizes the situation. Public figures should use social media to post informative updates that could help to reduce stigma, prejudice, discrimination, and inequalities related to Covid-19. (Mukhtar, 2021).

A study examined 81 peer-reviewed empirical studies relating to COVID-19 and social media from November 2019 to November 2020. (Tsao et al., 2021) Five overarching public health themes were identified concerning the role of online social media platforms and COVID-19: surveying public attitudes, identifying infodemics, assessing mental health, detecting or predicting COVID-19 cases, and analyzing government responses to the pandemic. (Pian et al., 2021) Furthermore, the review highlighted the paucity of studies on the application of machine learning on data from COVID-19-related social media and a scarcity of studies documenting real-time surveillance that was developed with data from social media on COVID-19 (Chen et al., 2022). Social media can be used to explore multiple facets of public health research, such as content analysis, surveillance, engagement, recruitment, as part of an intervention, and network analysis of users. (Pang et al., 2021)

A systematic review identified 12 topics related to COVID-19 on Twitter, categorized into four main themes: the origin, source, effects on individuals and countries, and methods of decreasing the spread of SARS-CoV-2. (Tsao et al., 2021) Social media can also effectively communicate health information to the general public during a pandemic. Analyzing and disseminating information from peer-reviewed, published research can guide policymakers and public health agencies to design interventions for accurate and timely knowledge translation to the general public. (Schmidt et al., 2022) This study aimed to understand social media's roles since the beginning of the COVID-19 crisis. It investigated public attitudes and perceptions towards COVID-19 on social media, information about COVID-19 on social media, the use of social media for prediction and detection of COVID-19, the effects of COVID-19 on mental health, and government responses to COVID-19 on social media. (Tsao et al., 2021)

The emergence of the Coronavirus 2019 (COVID-19) pandemic has caused a shift in economics, disruption in education, and various rules on home confinement. (Rocha, 2021) This disruption has led to the need for new information about the virus, clinical manifestations, transmission, and prevention of the disease (Adhikari et al., 2020). The rapid implementation of these measures, together with the number of significant deaths caused by the virus, has caused uncertainty in the population, leading to social and psychophysiological disorders (Clemente-Suárez et al., 2020) and reduced immunity (Lingam and Suresh Sapkal, 2020).

The World Health Organization (WHO) has worked closely to track and respond to the most prevalent myths and rumors that can potentially harm public health. A systematic literature review aimed to evaluate the impact of the media and the media during the pandemic caused by the new coronavirus, and to determine how the spread of infodemic impacts people's health (World Health Organization, 2020). (Pian et al., 2021) The infodemic's major causes were social media use, health/e-health illiteracy, and rapid publication services. In addition, spreading rumors led to anxiety, distress, fear, and other psychological issues that emerged as a characteristic of the infodemic.

The spread of false news and conspiracy theories during the COVID-19 pandemic has been a genuine concern among social-media platforms and governments. (Rocha, 2021) To contain the advance of fake news (FNs), Facebook has implemented a new feature to inform users when they engage with unverified information. Additionally, authorities and public agencies have been encouraged to discuss actions to mitigate the spread of conspiracy theories, and users are encouraged to flag inappropriate content to social-media companies (Krishnan et al., 2021). The impact of denial and its association with fake news presents itself as a social phenomenon, with good examples being the emergence of the earthmoving movement, the global warming farce, and anti-vaccination discourses. (Borges do Nascimento, 2022) When analyzing the phenomenon of fake news in health, it is possible to observe that infodemic knowledge is part of people's lives worldwide, causing distrust in Governments, researchers, and health professionals. The potential risks of misinformation include panic, depression, fear, fatigue, and the risk of infection, which can directly impact people's lives and health (Egelhofer and Lecheler, 2019).

In the COVID-19 pandemic, the disposition to spread incorrect information or rumors is directly related to the development of anxiety in populations of different ages (Sun et al., 2020). Overall, spreading false news and conspiracy theories during the pandemic has been a significant concern, leading to implementing strategies to contain misinformation and fake news (Pulido et al,. 2020). Social media platforms have contributed to the spread of false news, and the potential risks of misinformation can directly impact people's lives and health (Rocha, 2021). Additionally, Facebook has implemented a new feature to inform users when they engage with unverified information.

2.8 Egypt during The Pandemic

COVID-19, which originated in Wuhan, China, quickly infiltrated the world at the end of 2019 and, by the cusp of 2020, had become declared a pandemic. Created by the prevalence of social media, what came as a result of the pandemic was an "infodemic,"; meaning a spread of confusion and unreliable information sources that led to worldwide panic. (Marshall, Wesley & Correa, Eugenia,2021)

The first positive case reported in Egypt was in February (El Baradei et al., 2021), and since then, numbers have continued to rise while contradicting rumors have been spreading online. According to an official world census, the number of affected people doubled from June 2020 to November 2020, rising from 46,289 cases, 1,672 deaths, and 12,329 recoveries to 109,422 positive cases, 6,380 deaths, and approx. One hundred thousand recovered cases (Worldometer, 2022).

According to a report by the Egyptian National Telecom Regulatory Authority (NTRA), both home internet and the spread of the coronavirus pandemic rose dramatically from “mid-march to mid-April (El Baradei et al., .2021). Interestingly, almost none of the government websites mentioned the pandemic and had failed to be updated, with some exceptions. For example, the State Information Service (SIS) website featured some reassuring news articles detailing government efforts to combat the disease’s local spread (El Baradei et al., 2021) (sis.gov.eg, April 7, 2020). However, while there was little governmental presence on their official links, portals, and websites, El Baradei explains that there was no shortage of updates on the virus’s spread and containment efforts on Facebook and Twitter; but mostly the former. (El Baradei et al., 2021) On Facebook, the main governmental speakers during the pandemic were The Ministry of Health and Population (MoHP), the Official Presidency spokesperson, and the Armed Forces spokesperson. The FB page of the MoHP at the time of observation, 2021, sitting upwards of 4 million likes and 7.6 million followers and is the most recently created page; in January 2020 (El Baradei et al., 2021). This page will be the main focus of our study and the source of the data collected.

El Baradei’s (2021) aim in this study was to see how well the government was communicating in formation with the public during COVID-19. To do that, the MOHP Facebook page was mined for data using “CrowdTangle” by which the data was coded and analyzed using the RCCE model to conclude that the Egyptian government was effective in communicating information to the public during COVID-19; however, it could improve on issues of transparency.

2.9 Sentiment Analysis

Sentiment analysis is a research closely related to computational linguistics focusing on the sentimental analysis of written texts. Other names include “subjectivity analysis” or “opinion mining”. It is usually used to analyze informal texts for blogs, tweets, film reviews/ratings, and other statements on social media. It seeks to understand subjective elements in the text, such as linguistic expressions, using tools from data mining and computational linguistics. (Soleymani et al., 2017).

Sentiment analysis of the text is divided into two categories: explicit and implicit. Explicit sentiment analysis looks for subjectivity directly expressed as an opinion in a statement. On the other hand, implicit sentiment analysis is when the text implies an opinion. Most work in sentiment analysis has focused on explicit sentiment analysis, as it is easier to analyze (Mejova, 2009).

Moreover, sentiment polarity can be divided into positive and negative. However, it can also be thought of as a range. The strength of sentiment and the target of sentiment are also essential considerations in sentiment analysis. Sentiment analysis has been widely applied to product and movie reviews but can also be applied to other types of text, such as political commentaries and news articles. (Wang et al., 2020)

The goals of Sentiment Analysis include several separate tasks, which are usually combined to produce knowledge about the opinions found in the text. The first task is sentiment or opinion detection, which involves classifying text as objective or subjective, often conducted by inspecting the adjectives and adverbs in sentences. The second task is polarity classification, the analysis phase that classifies whether an opinionated piece of text has a positive or negative sentiment or whether the statement is objective. This task can be done at several levels. These levels can range from analysis at the term level, phrase level, sentence level, or document level. The third task that is complementary to sentiment identification is the discovery of the target of the sentiment, which can be an object, concept, person, or anything else. This task is particularly effective in analyzing product and movie reviews, where it is easy to identify the topic of the text (Birjali et al., 2021).

Various methodologies are used to achieve the aforementioned goals of sentiment analysis research. These methods most commonly include machine learning and part-of-speech tagging, two powerful and practical tools for classifying text according to sentiment. (Nerabie et al., 2021) Moreover, sentiment analysis tasks often involve classification, in which machine learning offers many algorithms for this purpose. However, this task presents unique challenges, such as choosing the correct variables to analyze to get the most accurate reading of the sentiments in the data. One notable discussion that researchers indulge in to determine sentiment is term presence vs. frequency. Some believe it is more beneficial to seek out unique terms rather than the most frequent ones. (Ahmet and Abdullah, 2020) Another feature is n-grams, in which researchers consider the position of terms in the text and their context. Other methodologies include topic-specific and cross-topic analysis (Chiril et al., 2022).

Sentiment analysis is often rooted in a lexicon or a lexical data base pertaining to a language. There are many different lexicons developed for research on analysis. What a lexical database contains are a list of words (nouns, verbs, adjectives) and all their synonyms, referred to as “synsets”. These words and their synsets are then linked to their sentiment: positive, negative, or objective (Xu et al., 2022). In later stages of the development of lexicons, they became more adapted in the analysis by not only giving a reading, but also, a rating of “intensity” and “centrality”. Intensity refers to the strength of the term (i.e. like, love, adore) and the centrality refers to the degree of relatedness to the sentiment, i.e., positive or negative (Verma, 2022). WordNet is good example of a lexical database still utilized today in sentiment analysis via the integration of coded-script algorithms that apply to the database on texts to be analyzed. There is no shortage of lexicons for the English language. However, it is not the case for other languages, especially Arabic (Areed et al., 2020).

In this research, a locally developed machine learning algorithm was fed a large set of Arabic manually annotated samples to create an auto-sentiment analysis tool fit for analyzing 18 different dialects of Arabic data mined from Facebook comments on the MOHP page.

CHAPTER 3: THEORETICAL FRAMEWORK

3.1 THEORETICAL FRAMEWORK:

To determine the framework for the research, the researcher must begin by defining social media's impact on public opinion and how it is measured. Moreover, how social media has added an avenue for expressing an opinion. Furthermore, the thesis discusses the results of auto-sentiment analysis, the resulting indications about public opinion, and how this relationship pans out in times of crisis or mass panic.(Dziewornu-Norvor, Woelinam. ,2022)

3.1.1 Social Media and Public Opinion

There have been many definitions for social media due to its rapid evolution and increasing variety of applications. Kaplan and Haenlein’s definition of social media is “a group of internet-based applications that build on the ideological and technological foundations of the Web 2.0, and that allow the creation and exchange of User Generated Content” (Kaplan and Haenlein, 2009, p. 61). Furthermore, Kaplan and Haenlein also provide a categorical breakdown of social media into blogs, content communities, social networking sites, virtual game worlds, etc. Facebook is still the predominant social media application, with 2.9 billion active users (Allen, 2022).

Social Media's spread and growth have changed how we perceive and measure public opinion. Consequently, mapping out accurate sentiments about public opinion became more challenging as it increased the speed of life and sentiment changes within the public sphere (Chung et al. 2022). Dr. Chung et al. state that public opinion is "the ideas, thoughts, expressions, interests, or beliefs of particular people part of broader society". "Polling" has long been the leading method to measure public opinion. However, due to elections such as the 2020 South Korean and the 2016 US elections, predictability using polls has no longer been descriptive (Gorodnichenko et al., 2021). In both elections, the readings from the polling efforts read in favor of the losing candidate (Gorodnichenko et al., 2021) (Norpoth, H., 2016).

To combat this inaccuracy, journalists have developed a more diversified approach to analyzing and describing public opinion. Dubois et al. (2020) describes a three-step analysis. The first level of analysis is at the 'quote' level. It aims to give a chance for the sentiment to be captured directly from words spoken by individuals through on-air calls, public interviews, and more. The second level of analysis is the 'trend'. Here, the journalists will report public reactions and responses, looking at the number of posts or trending topics. At the third level, the journalists look for the 'sentiment'. The objective at this stage is semantic polling, gathering social media data from the public and analyzing, quantifying, and graphing the data to make inferences about the sentiments displayed by the public. (Dubois et al. 2020). These strategies are tools that journalists use to explore public opinion, and the insights they garner are naturally attractive to the public. However, governments also resort to semantic polling to review their performance on specific issues.

3.0.2. Social Media and Public Opinion: Media Effects Theory

Social media has become an integral part of our daily lives, and it has a significant impact on public opinion. The Media Effects Theory explains how media can shape the attitudes and beliefs of people. This section will discuss Social Media and Public Opinion with a focus on the Media Effects Theory. We will explore the role of social media in shaping public opinion and how the Media Effects Theory explains this relationship. (Okocha, Desmond ,Ebi, Aihunume Oghegbuan., 2022)

3.0.3. Social Media and Public Opinion:

Social media has become a significant source of information for people. According to Pew Research Center (2021), about 72% of US adults use social media, and around 45% of them get their news from social media platforms. This shows how social media has become an important source of information for people and how it can influence their opinions and attitudes. (Auxier, Anderson,2021)

Social media allows people to share their opinions and thoughts with others, making it a platform for people to express their views and shape public opinion. Social media is not only used to express opinions, but it is also used to influence the opinions of others. Social media influencers, for example, have a significant impact on the opinions and attitudes of their followers. They can shape the public opinion by sharing their views on various issues and encouraging their followers to adopt those views.

The Media Effects Theory explains how media can influence the attitudes and behaviors of people. According to the theory, media has a powerful influence on people, and it can shape their opinions and beliefs. The theory suggests that media has four main effects on people: cognitive, affective, behavioral, and attitudinal (Bryant, & Oliver, 2009).

Cognitive Effects:

Media can shape the cognitive process of people by influencing how they think and perceive the world. Media can shape people's opinions and attitudes by providing them with information and shaping their perceptions of reality. Social media, for example, can shape the cognitive process of people by providing them with information on various issues and shaping their perceptions of those issues.

3.0.4 Affective Effects:

Media can influence the emotions and feelings of people. Media can evoke emotional responses in people, and it can shape their attitudes and beliefs based on those emotional responses. Social media, for example, can evoke emotional responses in people by providing them with content that triggers their emotions. This content can shape their attitudes and beliefs on various issues.

3.0.5 Behavioral Effects:

Media can influence the behavior of people. Media can shape people's behavior by providing them with information and shaping their perceptions of reality. Social media, for example, can shape the behavior of people by providing them with information on various issues and encouraging them to adopt certain behaviors.

3.0.6 Attitudinal Effects:

Media can influence the attitudes of people. Media can shape people's attitudes by providing them with information and shaping their perceptions of reality. Social media, for example, can shape the attitudes of people by providing them with information on various issues and encouraging them to adopt certain attitudes.

3.0.7 Examples of Social Media and Media Effects Theory:

The impact of social media on the 2016 US presidential election is an example of how social media can shape public opinion. Pew Research Center (2021) reported that social media played a significant role in the 2016 US presidential election. The study found that social media was used by both candidates to communicate with voters and to shape public opinion. Social media was also used to spread misinformation, which had a negative impact on the election.

The Black Lives Matter movement is another example of how social media can shape public opinion. The movement gained momentum in 2020 after the death of George Floyd, and social media played a significant role in its success (Delli Carpini, & Williams, 2018). Social media was used to spread information about the movement and to mobilize support for it. Social media also helped to raise awareness of police brutality and racial injustice, which led to widespread protests.

The impact of social media on public opinion during the Covid-19 pandemic is another example of how social media can shape public opinion. Social media has been used to spread information about the pandemic, to promote positive behaviors such as wearing masks and social distancing, and to criticize government responses to the pandemic (Centers for Disease Control and Prevention, 2020).

3.0.8 Conclusion:

Social media has become an integral part of our daily lives, and it has a significant impact on public opinion. The Media Effects Theory explains how media can shape the attitudes and beliefs of people (Bryant & Oliver, 2009). Social media has cognitive, affective, behavioral, and attitudinal effects on people. Social media can shape the cognitive process of people by providing them with information and shaping their perceptions of reality. Social media can trigger emotional responses in people, which can influence their attitudes and opinions. Social media can shape the behavior of people by providing them with information and encouraging them to adopt certain behaviors. Social media can shape the attitudes of people by providing them with information and encouraging them to adopt certain attitudes.

Media effects theory deals with how the media can shape people's perceptions and attitudes by presenting a particular perspective or information. (Stroud, 2011) Social media can be seen as a form of media, and as such, it has the potential to influence people in similar ways. However, social media also differs from traditional media in essential ways, such as the active participation of users in creating and sharing content and the ability to target specific audiences through algorithm, which can lead to different effects on individuals and society (Vargo & Guo, 2017). Additionally, social media's ability to facilitate the spread of misinformation and echo chambers can lead to negative consequences, such as the formation of false beliefs and polarization. (Valkenburg et al., 2016).

3.0.9 Social Media and Public Opinion: Social Cognitive Theory

Social media has become a ubiquitous part of modern life, shaping how we interact with one another and influencing how we perceive the world around us. In recent years, there has been growing interest in the role of social media in shaping public opinion, particularly in relation to significant events such as the Covid-19 pandemic. This section explores the role of social media in shaping public opinion from the perspective of the Social Cognitive Theory (SCT), and its application to the Covid-19 pandemic.

The Social Cognitive Theory (Bandura, 1986) posits that individuals learn through observation, modeling, and the reinforcement of behavior. According to this theory, social media can influence public opinion in several ways (Luszczynska, 2015). Firstly, social media provides individuals with access to diverse information sources, allowing them to observe and learn from others' behaviors and attitudes. Secondly, social media provides a platform for modeling behavior and attitudes, with individuals' actions and opinions frequently reinforced by others' engagement with their posts. Finally, social media algorithms can amplify certain behaviors and attitudes, shaping individuals' perceptions of what is socially acceptable and desirable (Lin et al., 2020). The theory also highlights the role of self-regulation in learning and how self-regulatory processes such as self-evaluation, self-reaction, and self-observation can be influenced by the information and feedback available on social media (Saleem et al., 2021).

3.1.1 Cognitive Effects of Social Media on Public Opinion

Social media has cognitive effects on public opinion through the information individuals are exposed to. Social media is a powerful tool for disseminating information, with individuals exposed to a wide range of content from multiple sources. This can shape individuals' perceptions of reality and influence their opinions on a range of issues, including the Covid-19 pandemic. For example, during the pandemic, social media played a significant role in disseminating information about the virus, including information on symptoms, prevention measures, and government policies. This information, whether accurate or not, can influence individuals' perceptions of the pandemic and their willingness to adhere to public health guidelines. (Bozzola, E., Spina, G., Agostiniani, R., Barni, S., Russo, R., Scarpato, E., Di Mauro, A., Di Stefano, A. V., Caruso, C., Corsello, G., & Staiano,2022)

3.1.2 Affective Effects of Social Media on Public Opinion

Social media has affective effects on public opinion through the emotions that individuals experience. Social media can trigger emotional responses, such as anger, fear, and sadness, which can influence individuals' attitudes and opinions. For example, during the Covid-19 pandemic, social media played a significant role in disseminating emotional content, including images and videos of healthcare workers and patients. This emotional content can shape individuals' perceptions of the pandemic and their attitudes towards healthcare workers and government policies. (Zhao,Zhou, 2020).

3.1.3 Behavioral Effects of Social Media on Public Opinion

Social media has behavioral effects on public opinion through the behaviors that individuals adopt. Social media can shape individuals' behavior by providing them with information and encouraging them to adopt certain behaviors. For example, during the Covid-19 pandemic, social media played a significant role in encouraging individuals to adopt behaviors such as social distancing, wearing masks, and washing hands regularly. This information and encouragement can shape individuals' behavior and influence their willingness to adhere to public health guidelines. (Yassin, AlOmari, Al-Azzam, Karasneh, Abu-Ismail, Luai, Soudah, 2021).

3.1.4 Attitudinal Effects of Social Media on Public Opinion

Social media has attitudinal effects on public opinion through the attitudes that individuals adopt. Social media can shape individuals' attitudes by providing them with information and encouraging them to adopt certain attitudes. For example, during the Covid-19 pandemic, social media played a significant role in shaping individuals' attitudes towards government policies, healthcare workers, and other individuals' behaviors. Social media can shape individuals' attitudes through the content that they are exposed to, as well as through the reinforcement of certain attitudes by others. (Han, Xu, 2022).

3.1.5 Application to the Covid-19 Pandemic

The Covid-19 pandemic has highlighted the significant role of social media in shaping public opinion. Social media has been used to disseminate information about the pandemic, including information on symptoms, prevention measures, and government policies. Social media has also been used to share emotional content related to the pandemic, including images and videos of healthcare workers and patients. Social media has encouraged individuals to adopt certain behaviors, such as social distancing, wearing masks, and washing hands regularly, while shaping their attitudes towards government policies, healthcare workers, and other individuals' behaviors. (Tsao, Chen, Tisseverasinghe, Yang, Li, Butt,2021)

However, the Covid-19 pandemic has also highlighted the potential negative effects of social media on public opinion. Social media has been used to spread misinformation and conspiracy theories about the pandemic, which can influence individuals' attitudes and behaviors. For example, social media has been used to spread false information about the effectiveness of vaccines, leading to vaccine hesitancy among some individuals. Social media has also been used to spread false information about the origins of the virus, leading to anti-Asian sentiment and discrimination. (Joseph, Fernandez, Kritzman, Eaddy, Cook, Lambros, , Jara Silva, Arguelles,Abraham,Dorgham, Gilbert., Chacko, Hirpara, Mayi, Jacobs,2022)

To address these negative effects, it is important to understand how social media influences public opinion and to develop strategies to mitigate its negative effects. One strategy is to promote media literacy and critical thinking skills among the public. This can help individuals to identify and resist misinformation and conspiracy theories, and to make informed decisions based on accurate information. Another strategy is to promote responsible social media use, including responsible sharing of information and respectful engagement with others' opinions. (Polanco-Levicán, Salvo-Garrido, 2022).

3.1.6 Conclusion

Social media has become a powerful tool for shaping public opinion, particularly in relation to significant events such as the Covid-19 pandemic. The Social Cognitive Theory provides a useful framework for understanding how social media influences public opinion through cognitive, affective, behavioral, and attitudinal effects. While social media can have positive effects on public opinion by disseminating accurate information, promoting healthy behaviors, and encouraging positive attitudes, it can also have negative effects by spreading misinformation and conspiracy theories. To mitigate these negative effects, it is important to promote media literacy and critical thinking skills among the public, as well as responsible social media use.

CHAPTER 4: PROPOSED MODEL AND METHODOLOGY

3.0 Research Questions

The research question is about the impact of social media on public perception of government COVID-19 response efforts in Egypt. The “impact” refers to the influence generated online in discussions about the topic. The research attempts to quantify this influence. The impact is different but related to the impression because it is not the first impression but the second. The public has a first, personal, and individual impression from announcements but the “impact” in the research questions refers to the second layer of perception on the first impression that social media reactionary tools and comments add. Social media is a vast platform that takes many forms, but for the sake of this study, Facebook will be the representative because it is the largest platform with the most users (Statista, 2022). When referring to the impact of social media, the question is inquiring about social media’s reactionary tools that the users use to react publicly to the posted content. These reactionary tools are written statements (comments and replies) and symbolic responses representing a range of reactions (likes and emoticons/emojis). A quantitative analysis of these reactionary tools (written statements and reactions) produces this research’s understanding of public perception. As mentioned, perception is the second impression realized during social media. The official response efforts represent the government's COVID-19 Response efforts report officially publicized by the Egyptian government through the MOHP Facebook page.

3.2 Sampling and Data collection:

Data in this study is gathered by Acumen[1] for this research from Facebook comments on the daily infographic COVID-19 statistics published on the official Facebook page of the Ministry of Health and Population. An algorithmic coded-script social data mining tool similar to "CrowdTangle," was used to collect data from the Facebook page's comments section about the infographic (Zhang et al., 2021). In addition to counting reactions and replies to comments, the algorithm is coded to transcribe the comment and assess it as a sentiment score using machine learning technology.

3.3. Sampling:

The sampling frame is the 52 weeks of 2020, from January to December. A random sample was taken each week, with one to nine direct comments and the reactions and responses to this comment. Each week, the computer processor generates three sequential draws of single-digit(s) random numbers. The first draw indicated the number of days to select from that week, one to seven. The second draw indicated which days to look at. One to seven meant Sunday to Saturday, respectively. If the first draw was four, the second draw generated four random numbers (from 1 to seven without replacement) to decide the days to pick. For each day picked, the third random number indicated how many comments to consider. Sometimes the third random number calls for some comments, say 9, when only three comments were posted on the designated day.

The rationale behind this sampling is to create a representative, quantifiable, and measurable depiction of sentiment of social media traffic. From there, we can begin to draw conclusions about the types of reactions the public expressed as a whole and how that affects their perception of the MOHP efforts in combatting the COVID-19 pandemic. The three stages of random draws insure that the results were not collected subjectively and that the researcher had no role in the selection of what data. It also insures that the data is adequately representative of the whole

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[1] Acumen (www.acumen.me), established in Egypt in 1997 and Dubai in 2001 to document, archive and analyze media in the MENA region. Acumen is a leader of electronic content from MENA, having the unrivalled distinction of owning four digitization, documentation, indexing and archiving centers – media, advertisements, law, and academic. Acumen supported this research by collecting the data and applying their machine learning algorithms to conduct the auto-sentiment analysis. The statistical analysis and presentation of results was done solely by the author.

population of Egypt without overwhelming the research with data pools that are too large to process.

3.4 Data Collection:

This process yielded a sample of 546 comments (rows). For each comment, *the search engine* generated 15 data items (columns): the user alias name, the number of comment replies to that post, the total number of reactions, the text of the comment, the post URL, the number of *like, love, haha, support, sorry, anger,* and *wow* reactions, the date and time the post was created, the auto-sentiment (+ve or –ve), and the auto-sentiment confidence. The researcher added the sixteenth column, called 'sentiment,' by multiplying the last two columns.

3.5 Reactions and Replies:

As mentioned before, the reactions are *like love, haha, support, sorry, anger*, and *wow*. The like emoji indicates a moderate level of approval with the comment. On the other hand, the *love* emoji symbolizes a more substantial agreement and embrace with the comment. When a comment is funny or laugh-worthy (perhaps in a cynical manner), the *haha* emoji is used. Moreover, when the comment sparks anger in a reader, they may respond with an *anger* emoji. It is important to note that the *anger* emoji is used on positive and negative comments as there may be strong opposition to online comments, especially in subjects relating to government performance.

Additionally, the wow emoji is used to indicate surprise or astonishment with a comment and may also be used sarcastically. The support emoji is like the like and love emojis. However, a more appropriate emoji corresponds to a call to action that is iterated in the comment (Goldenberg and Gross, 2020). Likes are usually the most used of these emojis, perhaps because it is the least invested response and because of online social pressure to conform (Asch, 1951).

Replies, therefore, present a more substantial degree of impact, by which the comment so moved the reader that they had responded in writing. The replies are not rated by sentiment, like the comment itself, so that they could be in agreement or disagreement. Nonetheless, replies are a strong indicator of an impactful impression compared to a reaction because there is a minority of people that misinterpret emojis and their intended meanings, causing them to use the wrong emoji to represent their reaction (Brants et al., 2015).

3.6 Total Engagement:

Total engagement refers to the cumulative reactions and replies to a given comment. As mentioned before, reactions and comments are not equal to an indication of impact; therefore, looking at one without the other is an incomplete assessment (Cinelli et al., 2020). This is why we combine them to compare comments to one another regarding impact on the public. Accordingly, this research begs the question of whether this impact displayed through reactionary emojis and written replies is correlated to the extremity of the comment (i.e., the auto-sentiment reading).

3,7 Auto-Sentiment:

The **auto-sentiment** is an Acumen AI algorithm that understands the comments based on machine learning to determine how positive or negative it is. The auto-sentiment assigns a positive or negative sign and a confidence score. The confidence score is between 0.5 and 0.99, indicating how confident the algorithm is of its assigned sign (0.5 means unsure, and 0.99 means very sure). The researcher multiplied the sign by the confidence score to obtain a single measure of the direction and its associated confidence. This measure, labeled 'sentiment', indicates how positive or negative the comment is as per the assessment of the AI algorithm.

3.8 Hypotheses:

Several studies attempted to justify aggressively commenting online based on de-individuation and disinhibition as two psychological processes that impel individual behavior, particularly under conditions of anonymity (Cho and Kwon, 2015; Claessens et al., 2003; McKenna and Bargh, 2000). Fewer studies suggest that “emotional contagion,” defined as ‘the process by which emotions unconsciously spread between people, often via emotional mimicry, a process in which we mimic others' emotional displays, and consequently, converge with their emotions' (Joby and Umemuro, 2022, p.157). This phenomenon can explain how aggressive reactions and comments can erupt and spread online. The social context theory of emotional mimicry in human-human interactions suggests that social factors, such as the group membership identities of interactants, modulate these processes. Exposure to highly negative or positive comments can stimulate similar comments and reactions and provoke sentiments via textual interactions and synchrony in linguistic expressions (Hancock et al., 2008; Kramer et al., 2014) and "language matching" (Gonzales et al., 2010 p. 3).

Emotional contagion in internet-based research showed how online emotional comments could be contagious, soliciting participation and empathy (Papacharissi, 2015). Emotional states can be effectively aroused and propagated by textual messages (Berger and Milkman, 2012; Kramer et al., 2014; Stieglitz and Dang-Xuan, 2013). The outbursts of emotion and extreme polarization rampant in today's parallel digital culture are worth greater scholarly attention.

Research on emotional group dynamics as an imminent contagious context highlighted two aspects of emotions. First, scholars investigated whether the valence of emotion – positive and negative – had dissimilar influences on the contagion progression. For instance, Orford (1986) reported that exposure to negative emotion intensifies the procession of negative social interactions. Barsade (2002) and Small and Verrochi (2009) report compelling support for negative and positive emotions contagion. While a few scholars found no valence difference (Steiglitz and Dong-Xuan, 2013), others indicated that positive online emotions sometimes significantly affect viral diffusion (Berger and Milkman, 2012; Gruzd et al., 2011; Gruzd, 2013). In contrast, Tseng and Huang (2016) found that in online ads containing depression-prevention messages, the narrator's positive or negative emotions directly affected the spectators' intent to embrace health risk-reducing behaviors.

The other essential aspect of interest is the intensity of arousal in emotion, also known as emotional energy (Yang et al., 2022) or emotional category activation (Berger and Milkman, 2012). Studying the Twitter platform (Stieglitz and Dang-Xuan, 2013) revealed that emotionally charged tweets were associated with significantly more retweeting. Crocamo et al., 2021) also showed that emotional category activation has a causal effect on the willingness to share online content. The literature on online internet cultures consistently reports a positive effect of emotional arousal on the contagion process. Based on the above, The following set of hypotheses are posited:

Hypotheses for Replies:

H1(A): The more positive the comment is, the more replies it receives.

H1 (B): The more negative the comment is, the more replies it receives.

Hypotheses for Reactions:

H2 (A): The more positive the comment is, the more reactions it receives.

H2 (B): The more negative the comment is, the more reactions it receives.

Hypotheses for Sentiment and Total Engagement):

H3: The more extreme the comment is, the more total engagement (replies and reactions) it receives.

H4: There will be more total engagement with negative comments than positive comments.

This research investigates the impact of social media on public governance during states of emergency such as a global pandemic. The case study chosen is Egypt in COVID-19. The social media platform being analyzed is Facebook. This research's hypotheses are organized by modes of assessment of the impact on social media: reactions, replies, and their combination, total engagement. The first and second hypotheses (H1a, H1b) predict that the more extreme the sentiment score (positive or negative) of the comment, the more replies it receives. If this is true, it would mean that the more outrageous and emotional a comment is, the more likely it is to impact public perception of how the government handles the pandemic. The third and fourth hypotheses (H2a, H2b) predict that the more extreme the sentiment score (positive or negative) of the comment, the more reactions it receives. If this is also true, it would further prove the correlation between the online extremity of expression and the impact of public perception online on the government.

Moreover, our fifth hypothesis (H3) predicts that total engagement online is directly correlated to the severity of the sentiment score of the comment. In other words, the more positive or negative a comment is, the more impact it has online on governance in times of crisis. The sixth and last hypothesis (H4) predicts that there will be more negative than positive online comments. If true, it could be indicative that the public perception of the Egyptian government's efforts to combat the pandemic was impacted negatively by social media.

The 'sentiment' score of the comment will be the independent variable in this research, and the dependent variables will be the 'number of replies' and the 'number of reactions to the comment. A simple regression model will be used to test the hypotheses.

CHAPTER 4: FINDINGS AND ANALYSIS

In the following sections, the data collected will be presented through descriptive statistics. Moreover, the data will be broken down and analyzed further through inferential statistics. The comments will be analyzed by sentiment, and the replies/reactions by frequency. The main aim will be to see how the severity of a comment's sentiment transpires online regarding reactions, replies, and total engagements during mass-panic and confusion.

4.1 EXAMPLE OF RANDOM POST FROM THE MOHP FACEBOOK PAGE

Below shows a random example of a post from the page of the MOHP Facebook page. It shows an example of what the MOHP posted from their Facebook address online and it is also the same place where people can comment, react, like, etc. What we see is a few statements about the total deaths, cured cases, new cases and total cases as well as a diagram with the numbers written on it.

facebook Sign Up

Email or pho

وزارة الصحة والسكان المصرية is sharing a COVID-19 update.

31 July 2020 ·

الصحة: ارتفاع حالات الشفاء من مصابي فيروس كورونا إلى 39638 وخروجهم من المستشفيات

الصحة: تسجيل 321 حالة إيجابية جديدة لفيروس كورونا.. و 31 حالة وفاة

أعلنت وزارة الصحة والسكان، اليوم، الجمعة، عن خروج 1402 متعاف من فيروس كورونا من المستشفيات، وذلك بعد تلقيهم الرعاية الطبية اللازمة وتمام شفائهم وفقًا لإرشادات منظمة الصحة العالمية، ليرتفع إجمالي المتعافين من الفيروس إلى 39638 حالة حتى اليوم.

وأوضح الدكتور خالد مجاهد مستشار وزيرة الصحة والسكان لشئون الإعلام والمتحدث الرسمي للوزارة، أنه تم تسجيل 321 حالة جديدة ثبتت إيجابية تحاليلها معمليًا للفيروس، وذلك ضمن إجراءات الترصد والتقصي والفحوصات اللازمة التي تُجريها الوزارة وفقًا لإرشادات منظمة الصحة العالمية، لافتًا إلى وفاة 31 حالة جديدة.

وقال "مجاهد" إنه طبقًا لتوصيات منظمة الصحة العالمية الصادرة في ٢٧ مايو ٢٠٢٠، فإن زوال الأعراض المرضية لمدة 10 أيام من الإصابة يعد مؤشرًا لتعافي المريض من فيروس كورونا.

وذكر "مجاهد" أن إجمالي العدد الذي تم تسجيله في مصر بفيروس كورونا المستجد حتى اليوم الجمعة، هو 94078 حالة من ضمنهم 39638 حالات تم شفاؤها، و 4805 حالات وفاة.

وتواصل وزارة الصحة والسكان رفع استعداداتها بجميع محافظات الجمهورية، ومتابعة الموقف أولاً بأول بشأن فيروس "كورونا المستجد"، واتخاذ كافة الإجراءات الوقائية اللازمة ضد أي فيروسات أو أمراض معدية، كما قاما الوزارة بتخصيص عدد من وسائل التواصل لتلقي استفسارات المواطنين بشأن فيروس كورونا المستجد والأمراض المعدية، منها الخط الساخن "105"، و"15335" ورقم الواتساب "01553105105"، بالإضافة إلى تطبيق "صحة مصر" المتاح على الهواتف ويمكن تحميله من خلال الرابطين التاليين:

نسخة اندرويد

https://bit.ly/2MHG97L

نسخة ايفون

https://apple.co/3gURgYJ

168K

8.9K comments 12K shares

4.1 DESCRIPTIVE STATISTICS

Three hundred thirty-five negative comments constituting 61% of the total comments were analyzed. On the other hand, two hundred and eleven comments (39%) were determined to have a positive sentiment.

4.1.1 Figure 1: Division of comments by Auto-sentiment (Pie Chart):

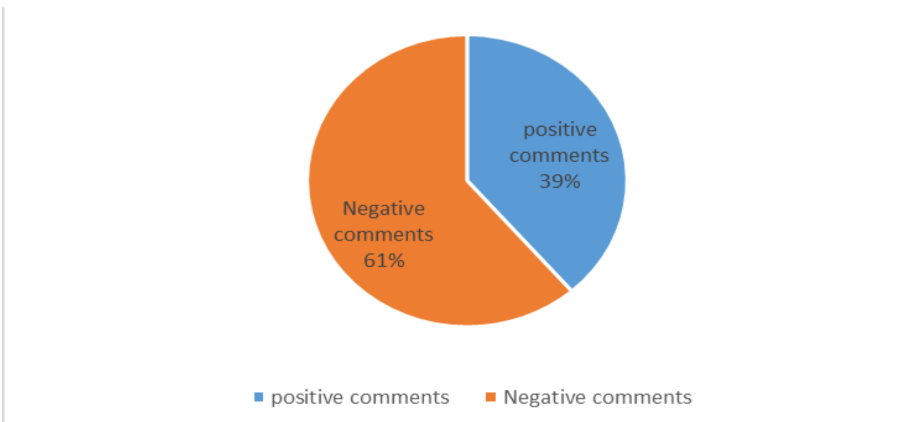
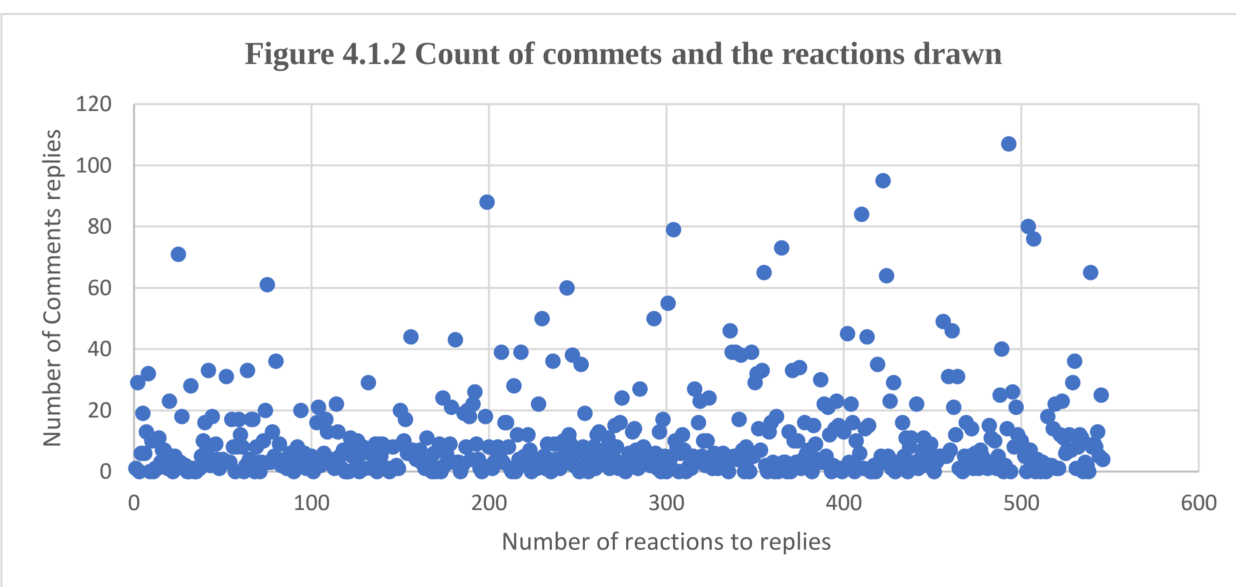


FIGURE 1

Figure 1 is a pie chart illustrating the division of comments by sentiment. This first observation shows that the majority of comments made online on the Facebook page of the MOHP were negative (61%), while the minority were positive (39%). This pie chart shows the abundance of negative comments over positive comments. The blue represents positive comments, as labeled



in the key, whereas the orange represents negative comments.

Figure 4.1.2 shows that the number of comments in any day ranges from 0 to about 100, and the reactions to any comment range from zero to about 550.

The following table 4.1.1 separates the positive and negative comments and shows the average number of reactions (total engagement) per positive or negative comment. We can see that the average engagement with positive comments is 80% more than the average engagement with negative comments. The analysis will statistically test this difference for significance.

Table 4.1.1 The average engagement per positive or negative comment.

Variable	Observations	Minimum	Maximum	Mean	Std. deviation
Total engagement with -ve Comments	335	1.000	358.000	42.976	53.066
Total engagement with +ve Comments	211	1.000	628.000	77.393	94.596

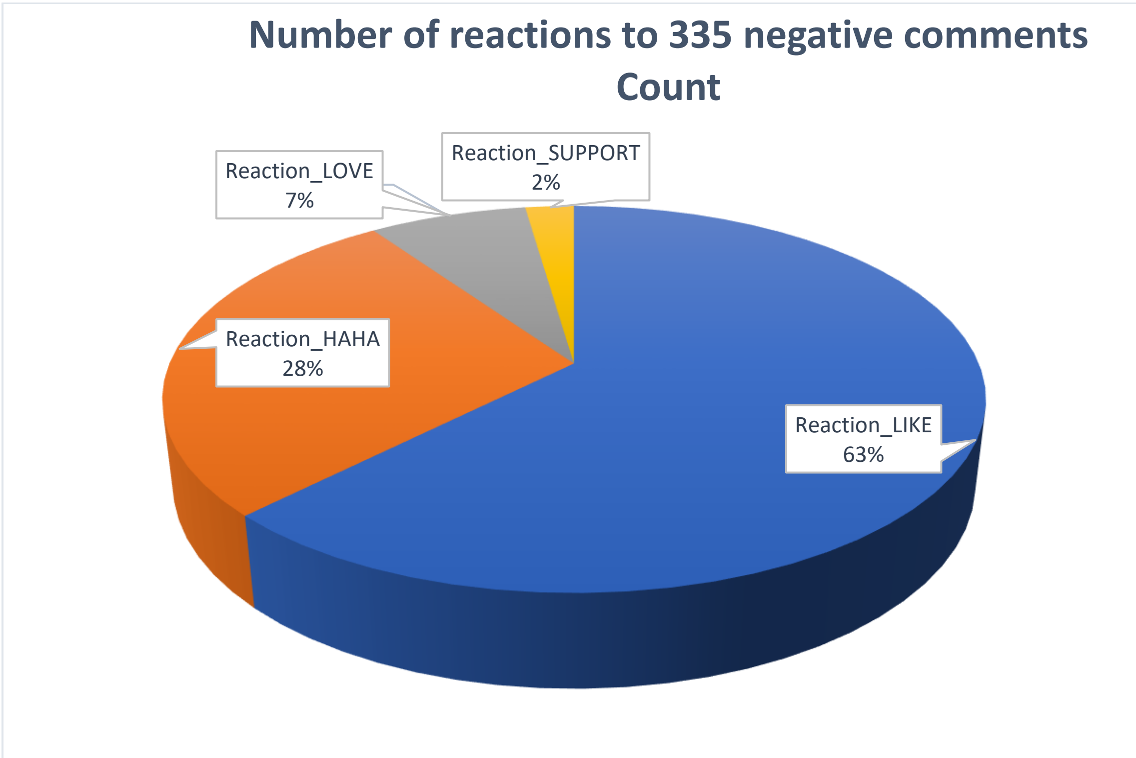
Table 4.1.2 below provides a granular view of the data, broken down by type of reaction and its prevalence for positive and negative comments. Note that none of the observed reactions were ‘sorry’, ‘anger’, or ‘wow’. The most popular reactions are ‘likes’, with about 65% of total reactions for both negative and positive comments. The second most popular reactions were ‘haha’, with more haha’s in reactions to negative comments (27%) than positive (20%) of total reactions. The third most popular reaction was ‘love’, which is lopsided toward being reactions to positive comments (15%) rather than to negative comments (7%).

Table 4.1.2 Type of reaction and its prevalence for positive and negative comments

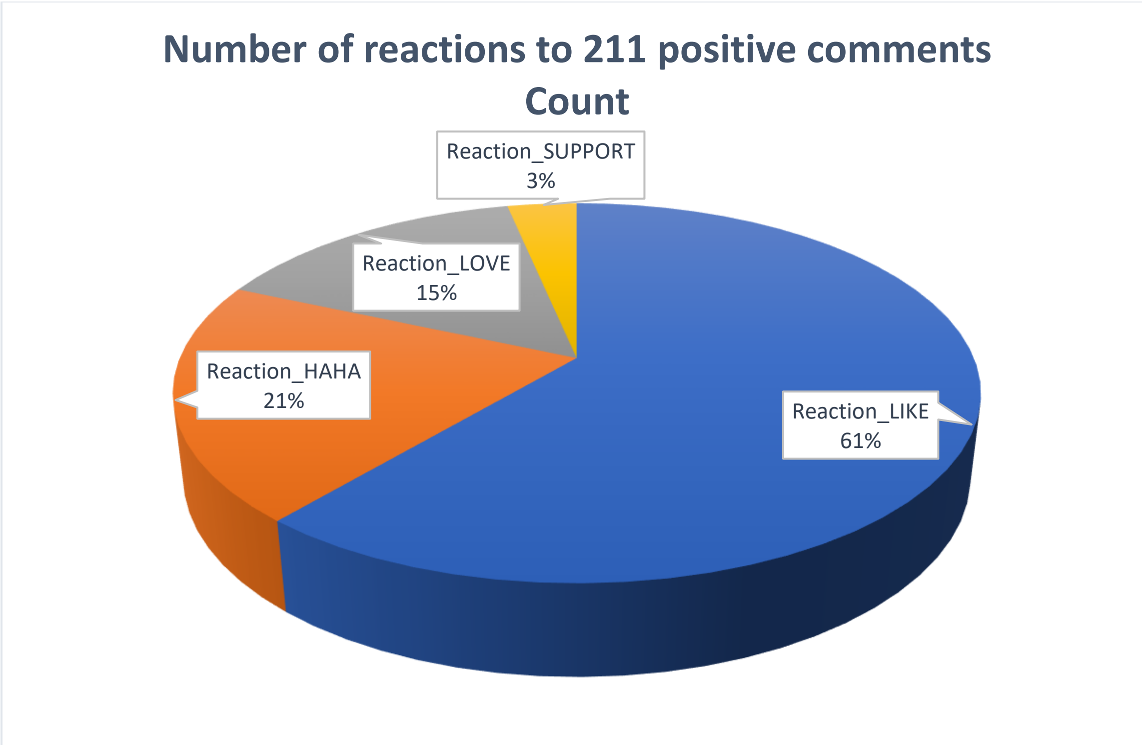
Type of Reaction	Number of reactions to 335 negative comments		Number of reactions to 211 positive comments		Total Reactions	
	Count	Average	Count	Average	Count	Average
Reaction_LIKE	6,922	19	8,188	39	15,110	72
Reaction_LOVE	820	2	2,023	10	2,843	13
Reaction_HAHA	3,084	9	2,723	13	5,807	28
Reaction_SUPPORT	253	1	443	2	696	3
Reaction_SORRY	0	0	0	0	0	0
Reaction_ANGER	0	0	0	0	0	0
Reaction_WOW	0	0	0	0	0	0

The following two figures (1.2 & 1.3) depict the division of reactions by comment sentiment. Here we see the most prevalent reactions on negative comments versus the reactions that are most present for positive reactions. We see that predominantly the reactions on both negative and positive comments are likes, which represents a moderate approval of the comment. The second most prevalent reaction in both comment types is the love reaction indicating a strong approval of the comments. The third most prevalent is the “haha” reaction, which indicates to us that they found the comment funny, satirical or other wise laugh-worthy. We should note that this reaction does not indicate whether the humor found was in agreement or disagreement with the comment. However, the fourth most used reaction, “support”, clearly states the agreement and full approval of the comment made.

4.1.2 Figure 1.2: Division of Reactions by Negative Comments (Pie Chart):



4.1.3 Figure 1.3: Division of Reactions by Positive Comments (Pie Chart):



4.2 INFERENTIAL STATISTICS

This section will report the results of testing the six hypotheses in this thesis.

H1(A):

The first hypothesis, H1(A), states that: The more **positive** the comment is, the more **replies** it receives. To test this hypothesis, a linear regression was conducted using XLSTAT using the positive sentiment score, ranging from 0.500 to 0.999 (where 0.500 is the least positive and 0.999 is the most positive) was used as the predictor variable. The dependent variable was the number of replies for each value positive sentiment. Table 4.2.1a presents the Summary statistics of the two variables, and Figure 3 is the graphical representation of the regression model.

4.2.1 Table 1a. Summary statistics (Replies/Positive Comments):

Variable	Observations	Minimum	Maximum	Mean	Std. deviation
comment_replies	211	0.000	107.000	12.995	18.054
Positive Sentiment	211	0.503	0.998	0.836	0.163

In Table 4.2.1a we can deduce that out of the 211 positive comments the maximum number of replies a single comment got was 107 and the average replies a comment got was around 13. The standard deviation of replies per positive comment is 18.054.

4.2.2 Table 1b. Analysis of variance (Replies/Positive Comments):

Source	DF	Sum of squares	Mean squares	F	Pr > F
Model	1	38184.025	38184.025	112.003	<**0.0001**
Error	210	71592.975	340.919		
Corrected Total	211	109777.000			

A one-way ANOVA was performed to compare the effect of the positive sentiment scores on replies.

A one-way ANOVA revealed that there was a statistically significant difference in replies between at least two groups (F(between groups df, within groups df) = [1,210], p = [<**0.0001**]).

4.2.3 Table 1c. Model parameters (Replies/Positive Comments):

Source	Value	Standard error	T	Pr > |t|	Lower bound (95%)	Upper bound (95%)
Intercept	-1.000					
Positive Sentiment	15.799	1.493	10.583	**<0.0001**	12.856	18.741

Equation of the model: Comment_replies= -1+15.799*Positive sentiment

4.2.4 Figure 2. Graphic Representation of Regression model (Replies/Positive Comments):

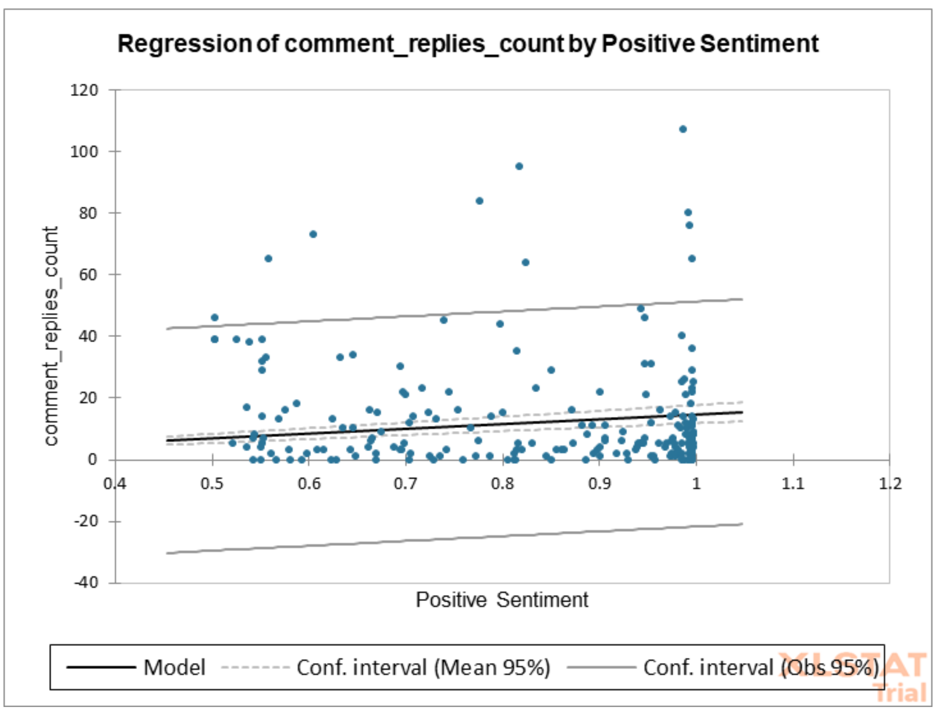


FIGURE 2

H1(A) is strongly supported, as the regression model showed that positive sentiment scores predicted the number of replies, R2 = .348, F(1, 210) = 112.003, p <.0001. More positive sentiments triggered significantly more replies than less negative sentiments, $t(210) = 10.583$, $p < 0.0001$, 95% CI [12.856, 18.741].

H1(B):

The second hypothesis, H1(B), posits that the more **negative** the comment is, the more the number of **replies** it receives. To test this hypothesis, a linear regression was conducted using XLSTAT using the negative sentiment score, ranging from -0.500 to -0.999 (where -0.500 is the least negative and -0.999 is the most negative) was used as the predictor variable. The dependent variable was the number of replies for each negative sentiment value. Table 3 presents the Summary statistics of the two variables, and Figure 2 is a graphical representation of the regression model.

4.2.5 Table 2a. Summary Statistics (Replies / Negative Comment) :

Variable	Observations	Minimum	Maximum	Mean	Std. deviation
Comment_replies	335	0.000	88.000	8.904	12.334
Negative Sentiment	335	-0.999	-0.501	-0.789	0.141

In Table 2a, we can deduce that out of the 335 negative comments, the maximum amount of replies a single comment got was 88, and the average number of replies a comment got was around 9. The standard deviation of replies per negative comment is 12.334.

4.2.6 Table 2b. Analysis of variance (Replies / Negative Comments):

Source	DF	Sum of squares	Mean squares	F	Pr > F
Model	1	31341.375	31341.375	200.021	**<0.0001**
Error	334	52334.625	156.690		
Corrected Total	335	83676.000			

A one-way ANOVA was performed to compare the effect of the positive sentiment scores on replies. The one-way ANOVA revealed a statistically significant difference in replies between at least two groups (F(1, 334) = 112.003, p = **<0.0001**).

4.2.7 Table 2c. Model parameters (Replies/Negative Comment):

Source	Value	Standard error	t	Pr > |t|	The lower bound (95%)	Upper bound (95%)
Intercept	-1.000					
Negative Sentiment	-12.065	0.853	-14.143	<**0.0001**	-13.743	-10.387

Equation of the model: Comment_replies = -1-12.065*Negative sentiment

4.2.8 Figure 3. Regression Plot for Comment replies versus Negative Sentiment (Replies / Negative Comments).

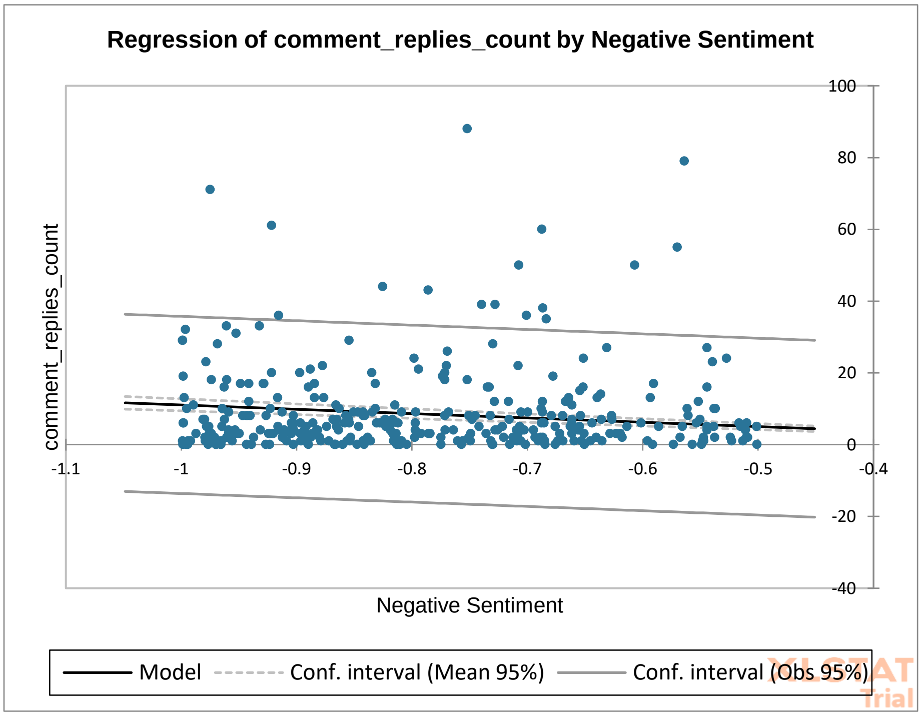


FIGURE 3

H1(B) is strongly supported, as the regression model showed that negative sentiment scores predicted the number of replies, R2 = .375, F(1, 334) = 200.021, p <.0001. More negative sentiments triggered significantly more replies than less negative sentiments, t(334) = -14.14, p<0.0001, 95% CI [-13.743, -10.387].

H2(A):

The third hypothesis, H2(A), states that: the more **positive** the comment is, the more the number of **reactions** it receives. To test this hypothesis, a linear regression was conducted using XLSTAT using the positive sentiment score, ranging from 0.500 to 0.999 (where 0.500 is the least positive and 0.999 is the most positive) was used as the predictor variable. The dependent variable was the number of reactions for each value positive sentiment. Table 5 presents the Summary statistics of the two variables and Figure 4 is the graphical representation of the regression model.

H2(A) is strongly supported, as the regression model showed that positive sentiment scores predicted the number of reactions, R2 = .384, F(1, 210) = 130.841, p <.0001. More positive sentiments triggered significantly more reactions than less positive sentiments, t(210) = 11.439, p <0.0001, 95% CI [63.598, 90.083].

4.2.9 Table 3a. Summary statistics (Reactions/Positive Comments):

Variable	Observations	Minimum	Maximum	Mean	Std. deviation
total_reactions	211	1.000	588.000	64.398	83.113
Positive Sentiment	211	0.503	0.998	0.836	0.163

In Table 3a, we can deduce that out of the 211 positive comments, the maximum amount of reactions a single comment got was 588, and the average number of replies a comment got was around 64. The standard deviation of reactions per positive comment is 83.113.

4.2.10 Table 3b. Analysis of variance (Reactions/Positive Comments):

Source	DF	Sum of squares	Mean squares	F	Pr > F
Model	1	903288.639	903288.639	130.841	**<0.0001**
Error	210	1449776.361	6903.697		
Total	211	2353065.000			

A one-way ANOVA was performed to compare the effect of the positive sentiment scores on reactions. The one-way ANOVA revealed a statistically significant difference in reactions between at least two groups ($F(1, 210) = 112.003$, p<**0.0001**).

4.2.11 Table 3c. Model Parameters (Reactions/Positive Comments):

Source	Value	Standard error	t	Pr > |t|	Lower bound (95%)	Upper bound (95%)
Intercept	-1.000					
Positive Sentiment	76.841	6.718	11.439	<**0.0001**	63.598	90.083

Equation of the model: Total_reactions = -1+76.841*Positive sentiment

4.2.12 **Figure 4. Graphic Representation of Regression Model of Comment Replies Versus**

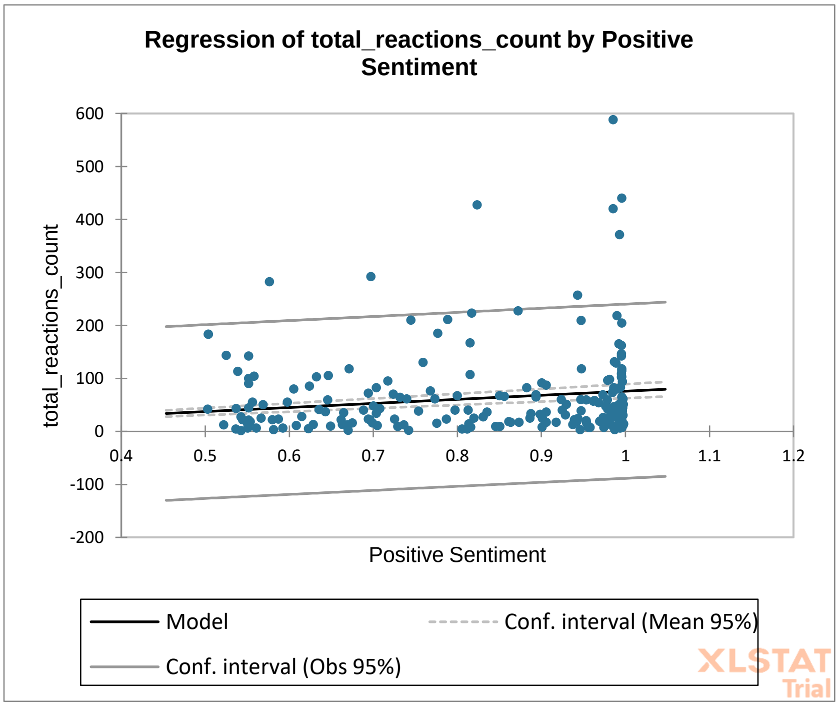


FIGURE 4

Positive Sentiment.

H2(B):

The fourth hypothesis, H2(B), states that: The more **negative** the comment is, the more the number of **reactions** it receives. To test this hypothesis, a linear regression was conducted using XLSTAT using the negative sentiment score, ranging from -0.500 to -0.999 was used as the predictor variable. The dependent variable was the number of reactions for each negative sentiment value. Table 6 presents the Summary statistics of the two variables, and Figure 4 is the graphical representation of the regression model.

4.2.13 Table 4a. Summary Statistics (Reactions / Negative Comments:

Variable	Observations	Minimum	Maximum	Mean	Std. deviation
total_reactions_	335	1.000	293.000	34.072	44.442
Negative Sentiment	335	-0.999	-0.501	-0.789	0.141

In Table 4a, we can deduce that out of the 335 negative comments, the maximum amount of reactions a single comment got was 293, and the average number of replies a comment got was around 34. The standard deviation of reactions per negative comment is 44.442.

4.2.14 Table 4b. Analysis of variance (Reactions / Negative Comments):

Source	DF	Sum of squares	Mean squares	F	Pr > F
Model	1	388253.100	388253.100	189.730	**<0.0001**
Error	334	683477.900	2046.341		
Corrected Total	335	1071731.000			

A one-way ANOVA was performed to compare the effect of the negative sentiment scores on reactions. The one-way ANOVA revealed a statistically significant difference in reactions between at least two groups ($F(1, 334) = 189.73$, p<**0.0001**).

4.2.15 Table 4c. Model Parameters (Reactions / Negative Comments):

Source	Value	Standard error	t	Pr > |t|	Lower bound (95%)	Upper bound (95%)
Intercept	-1.000					
Negative Sentiment	-42.4628	3.083	-13.774	<**0.0001**	-48.527	-36.399

y=a+bx

Equation of the model: Total Reactions = -1-42.4628*Negative sentiment

4.2.16 **Figure 5. Graphical Representation of the Regression Model.**

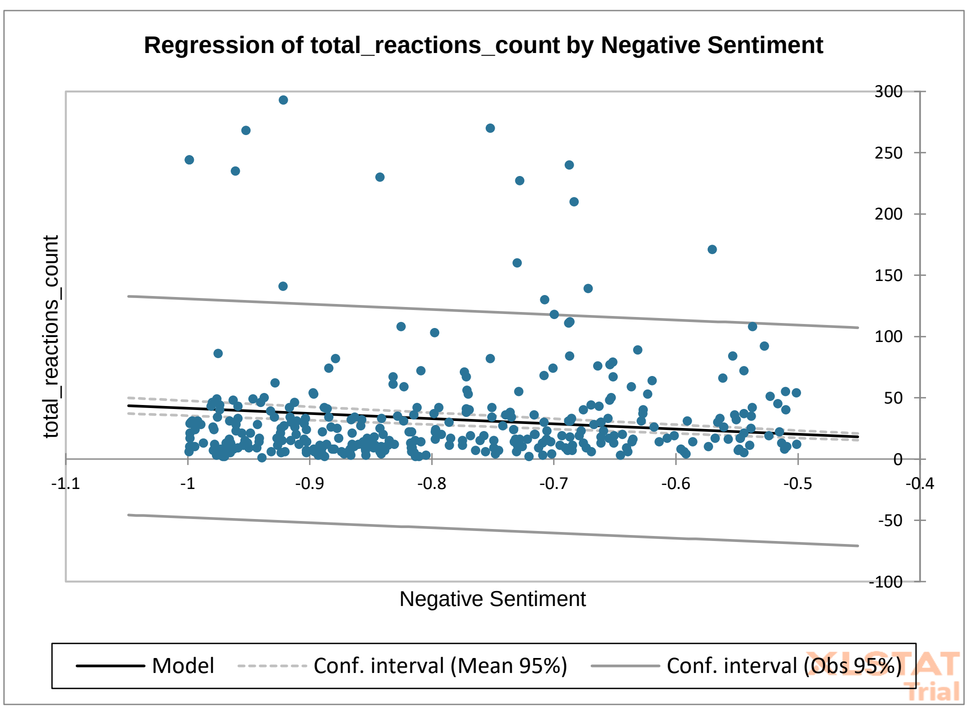


FIGURE 5

H2(B) is strongly supported, as the regression model showed that negative sentiment scores predicted the number of reactions, $R2 = .362$, $F(1, 334) = 189.730$, $p < .0001$. More negative sentiments triggered significantly more reactions than less negative sentiments, $t(334) = -13.774$, $p < 0.0001$, 95% CI [-48.527, -36.399].

H3:

The fifth hypothesis is H3 which posits that the more extreme the comment is (positive or negative), the total engagement (replies and reactions) it receives.

To test this hypothesis, a linear regression was conducted using XLSTAT using the sentiment score, ranging from 0.500 to 0.999, as the predictor variable. The absolute value was used for the negative sentiment scores, so all the scores could fit in one regression model. The dependent variable was the total number of engagements for each sentiment value, whether replies or reactions. Table 7 presents the Summary statistics of the two variables, and Figure 6 is the graphical representation of the regression model.

4.2.14 Table 5a. Summary Statistics (Total engagement)

Variable	Observations	Minimum	Maximum	Mean	Std. deviation
Total engagement	546	1.000	628.000	56.277	73.859
Absolute Sentiment	546	0.501	0.999	0.807	0.151

In Table 5a, we can deduce that out of the 546 comments, the maximum amount of total engagement a single comment got was 628 combined reactions and replies, and the average total engagement a comment got was around 56 combined reactions and replies. The standard deviation of engagement per comment is 73.859.

4.2.15 Table 5b. Analysis of Variance (Total engagement)

Source	DF	Sum of squares	Mean squares	F	Pr > F
Model	1.000	1761712.305	1761712.305	319.772	<**0.0001**
Error	545.000	3002556.695	5509.278		
Corrected Total	546.000	4764269.000			

A one-way ANOVA was performed to compare the effect of absolute sentiment scores on total engagement. The one-way ANOVA revealed a statistically significant difference in total engagement between at least two groups (F= 319.77, p = <**0.0001**).

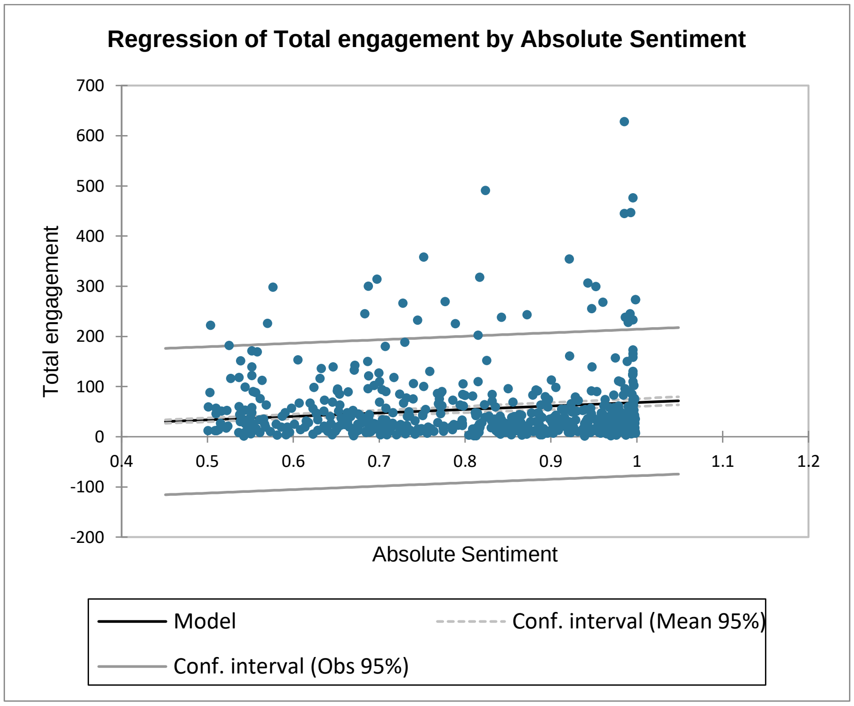
4.2.16 Table 5c. Model Parameters (Total engagement)

Source	Value	Standard error	t	Pr > |t|	The lower bound (95%)	Upper bound (95%)
Intercept	-1.000					
Absolute Sentiment	69.161	3.868	17.882	<**0.0001**	61.564	76.758

TABLE 5C

Equation of the model: Total engagement = -1+69.161*Absolute Sentiment

4.2.17 Figure 6: Regression of Total engagement by Absolute Sentiment



Given the R2, 37% of the dependent variable, Total engagement variance is explained by the explanatory variable Absolute Sentiment.

H4: There will be total engagement with negative comments than positive comments.

The sixth and last hypothesis is H4 which posits that there will be total engagement (replies and reactions) with negative comments than positive comments.

To test this hypothesis, a two-tailed t-test for the difference between two independent samples was conducted using XLSTAT. The total number of engagements, whether replies or reactions, for each positive sentiment value was compared to the total number of engagements for each negative sentiment. Table 8 presents the Summary statistics of the two variables and the results of the t-test.

4.2.18 Table 6a. Summary statistics (Total Engagement / Absolute Sentiment):

Variable	Observations	Minimum	Maximum	Mean	Std. deviation
Total engagement with -ve Comments	335	1.000	358.000	42.976	53.066
Total engagement with +ve Comments	211	1.000	628.000	77.393	94.596

4.2.19 Table 6b. t-test for two independent samples / Two-tailed test:

95% confidence interval on the difference between the means:

Difference	-34.417
t (Observed value)	-5.439
DF	544
p-value (Two-tailed)	**<0.0001**

The results show that the average number of total engagement for the positive comments (77,393) is significantly more than for negative comments, $t(544) = 5.439$, $p < .0001$. This result is against our hypothesis that there will be more total engagement (replies and reactions) with negative comments than positive comments.

Generally, our first five hypotheses were supported, while our sixth hypothesis was rejected and reversed.

CHAPTER 5: CONCLUSION, POLICY IMPLICATIONS, AND FUTURE RESEARCH

5.1 Conclusion and Discussion

The objective of this study was to examine the impact of social media on the public perception of government during a public crisis: COVID-19. This subject is essential because, during the COVID-19 pandemic, the mass panic was experienced worldwide (Anser, 2020). With some scientists predicting more pandemics, public policy officials must understand how to better communicate with the public to reduce panic in times of crisis (Katul, 2021).

Social media impacted public perception of government communication during the COVID-19 pandemic year (Angawi,Albugmi, 2022). Negative comments drew reactions and replies, and so did positive comments. This study aimed to shed light on the online interactions' effect on the public's perception of government performance. This study shows the aggregation characteristics of public opinion on social media in times of crisis and how it can negatively impact the perception of government online. We can draw the following conclusions from our analyses.

The more negative (or positive) the comment is, the more replies and reactions it receives. So extreme comments draw significantly more engagement than milder comments, as evident from our results for the first five hypotheses. Theories of emotional contagion and the psychological tendency to synchronize and converge emotionally offer some explanation why more extreme comments can trigger and propel reactions and replies online (Hatfield et al., 1993, p. 96-97).

One future direction for research is to test the propositions of Hancock et al. (2008) and Kramer et al. (2014) that exposure to highly negative or positive comments can stimulate similar comments and reactions and provoke sentiments via textual interactions and synchrony in linguistic expressions. This similarity has not been tested and can be done using content analysis for the replies versus the original comment.

Papacharissi (2015) posited that online emotional contagion exists and solicits participation and empathy. The results tested the valence (negative or positive) of the original comment but not its emotional disposition or textual messages (Berger and Milkman, 2012; Kramer et al., 2014; Stieglitz and Dang-Xuan, 2013). That is another area for future research to be considered using the qualitative linguistic approach to content analysis (Roberts, 1989). A result of that direction for future research is the remarkable polarization and emotional outbursts nowadays.

The other essential aspect worth exploring in future research is the intensity of arousal in emotion, also known as “emotional energy” (Barsade, 2002) or “emotional activation” (Berger and Milkman, 2012), shown to have a causal effect on the willingness to share online content. The literature on western online internet cultures consistently reports a positive effect of emotional arousal on the contagion process. It is foreseeable that a comparative study of the same effect in the middle-eastern context, with its natural tendency for emotional sensitivity.

The results did not support the last hypothesis that negative comments draw more engagement than positive comments. The hypothesis was founded on Orford's (1986) premise that exposure to negative emotions intensifies the procession of negative social interactions. Orford’s study was before the online era and culture, and it seems that the online context has different rules. Other scholars in the dawn of internet 2.0 reported strong support for online negative and positive contagion (Barsade, 2002; Small and Verrochi, 2009) or no valence difference (Steiglitz and Dong-Xuan, 2013). As social media matures, more recent research indicated that positive online emotions sometimes significantly affect viral diffusion (Berger and Milkman, 2012; Gruzd et al., 2011; Gruzd, 2013). Perhaps this shift is a potential area for a longitudinal literature review spanning the three eras: the offline, online, and social media realms.

5.2 Limitations

The bandwagon effect is a limitation in working with social media data regarding reactions and replies. One feature of the platform is that comments with the most reactions get propelled to the top of the list and thus continue getting more reactions due to their placement. This characteristic creates outliers and distorts means and other contingent statistical inferences.

Another limitation is the time allowed to finish the thesis, which left many exciting extensions open for future research. Given more time and resources, qualitative research would have enriched the discussion, mainly conducting focus groups with commentators and in-depth interviews with experts to gain insights, enrich the analysis, and bring context to the quantitative results.

The data is limited to one platform, Facebook. Facebook, by design, allows for collecting the data needed for this thesis, while other platforms, such as Twitter, would provide a different perspective, given its more intellectual and diverse nature. A future study could replicate the thesis in the other top platforms and explore the differences and similarities.

5.3 Policy Implications

El Baradei's (2021) research investigated how well the government informed the public about its efforts to combat the spread of the pandemic. This thesis adds another layer to the analysis by exploring the feedback and analyzing the public sentiment within the online ecosystem. It provides an added vista to aid public policymakers and government officials in making informed decisions by quantifying the environment of social media with all its aggregating traits. Lastly, the findings of this research can be used in further studies as a forecast of aggregation to the extreme when trying to describe the impact of social media on public perception in general.

The public's opinion is critical to supporting the policymakers' use of social customer-centric approaches to providing services, diffusing information, and sensing the people's pulse, particularly during times of crisis. The thesis may be a formidable source for government officials to understand the people's perspectives and hence, provide services that are up to their expectations. Moreover, the thesis demonstrates the ripple effect of people reacting to the initial comments of others they do not necessarily know. Sharing, commenting on, and reacting to comments create waves of second and third-hand public opinion that can shift the direction and divert, distract, and disturb the flow of information from one-to-many to a confusing many-to-many mode.(OECD,2005)

As government officials venture out of the protected e-government one-way communication to the we-government multi-way social media realm, they must be adept and learn the rules of that new world. First, government officials, all the way to the top position, become one voice overwhelmed and outnumbered in the open democratic discussion. Second, ranks and positions are shed at the login and replaced by an equal footing without control over who says what, when, and how. Third, agendas, ignorance, disrespect, vulgarity, and irrelevance are common and tolerated beyond the physical world thresholds.

Research has made significant progress regarding natural language processing and aspect-based sentiment analysis using government review data albeit the complications faced in such tasks (Alqaryouti et al., 2020). Every institution and business wants to be well-informed of its stakeholders' opinions (Taher, 2023), and sentiment analysis with machine learning and other artificial intelligence technologies will remain in high demand. Governments and parliaments are drawn to online engagement with their constituents and the public (Serra-Silva, 2022).

Perfect, automated, and precise solutions that can be applied to interpret and analyze all communications populating online public domains are yet to be developed. Nevertheless, there are programmed solutions where some tasks are automated while domain-specific aspects are manually annotated. Furthermore, the manual efforts in labeling data can be effectively reduced by applying cross-domain sentiment analysis, where the machine learns from a specific domain and applies the knowledge to analyze the sentiment of texts in other domains (Alqaryouti et al., 2020). Thus, while the thesis focuses on one domain, the methods applied are valid in other public and private service online spheres.

5.4 Policy Model

The proposed solution for the problems posed by social media's influence on public perception is not finally defined due to the unpredictable nature of social discourse online. However, this thesis advocates initiating ongoing awareness and educational campaigns to enlighten policymakers on how social media has the power to sway opinions unpredictably without logical justification. This training and awareness are critical at all times, especially in crises and elections, to reduce the threat of social media's potential chaotic impact. Failing to provide the proper research and logical foundation for government social media communication can work adversely by giving the public something to ridicule and reject. Therefore, public policy campaigns should only be undertaken after developing a complete understanding of pertinent public opinion issues and consulting with stakeholders to preempt and uproot potential communication debacles. (Johannessen, Sæbø, Øystein, Flak, 2016).

The governmental request for public restraint and critical thinking should be maintained with statistics that corroborate the necessity of this behavior change. This campaign will only work in the government's favor by convincing the public at a logical level. Furthermore, this thesis predicts that accessing an emotional or spiritual path to persuasion will not pan out well because it would be critiqued logically and deemed propaganda. (Sawicki,2016)

The suggested proposed model for times of crisis and confusion online is a 2-step model:

1- Government pages should ban any alias/anonymous comments on statistical/medical posts; meaning that any comments made on these pages should include the legal first and last name of the user commenting. This deters the proportion of emotional/anti-governmental narratives for entertainment, thus counteracting the compounding effects of social media. The idea is to give the comments more accountability without hindering the public’s freedom of speech. Now, users have to really mean what they say because their name is tied to it publicly. Additionally, it is a fast and efficient method of treatment because it plays within the realms of social media without having to censor, circumvent or confront social media tech giants like Facebook for solutions. In other words, in most platforms it is every page’s right to turn off comments, hold them for approval or let them show in real-time. It is a diplomatic, non-abrasive, non-confrontational method of reducing the aggregative characteristics of social media.

2- Using bots to purport the most positive comment by feeding it likes. This makes sure that no matter what the consensus is; a positive model of reaction is present and available for people to endorse. This may seem controlling or coercive, however, in times of crisis and mass-panic, a complete absence of any positive sentiments can be detrimental to keeping the peace and maintaining civil discourse.

Creating awareness campaigns that explain to the public the abilities of social media to distort reality during times of crisis are prone to produce contrary results; as asking people to “think” any certain way is not the job of the MOHP. Moreover, fragmenting or defragmenting the posts to isolate or dilute the online traffic is also prone to backfire, because too little communication leaves room for rumors and too much gives more opportunity for uncontrollable online discourse. On social media, the best form of government censorship is, sometimes, none (Samples, 2020).

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APPENDIX A: IRB APPROVAL

Appendix B: Data

Sentiment Score	comment replies count	total reactions count	Absolute Sentiment	Total engagement with -ve Comments	Total engagement with +ve Comments
-0.999	1	6	0.999	7	88
-0.999	29	244	0.999	273	222
-0.998	0	10	0.998	10	17
-0.998	6	29	0.998	35	182
-0.998	19	17	0.998	36	8
-0.998	6	21	0.998	27	60
-0.997	13	30	0.997	43	151
-0.996	32	31	0.996	63	34
-0.996	0	10	0.996	10	1
-0.995	10	28	0.995	38	30
-0.994	0	10	0.994	10	18
-0.994	1	24	0.994	25	6
-0.992	1	31	0.992	32	139
-0.989	11	28	0.989	39	26
-0.987	3	13	0.987	16	171
-0.981	7	43	0.981	50	122
-0.980	7	46	0.980	53	58
-0.979	2	26	0.979	28	25
-0.979	1	7	0.979	8	88
-0.979	23	24	0.979	47	169
-0.978	5	12	0.978	17	8
-0.976	0	3	0.976	3	25
-0.976	5	49	0.976	54	63
-0.976	3	34	0.976	37	298
-0.975	71	86	0.975	157	25
-0.974	3	44	0.974	47	3
-0.974	18	40	0.974	58	41
-0.973	1	8	0.973	9	6
-0.971	2	2	0.971	4	57
-0.970	0	2	0.970	2	153
-0.970	0	3	0.970	3	14
-0.968	28	13	0.968	41	31
-0.968	1	6	0.968	7	5
-0.966	0	16	0.966	16	98
-0.966	0	31	0.966	31	13
-0.965	1	10	0.965	11	136
-0.965	1	5	0.965	6	51

Sentiment Score	comment replies count	total reactions count	Absolute Sentiment	Total engagement with -ve Comments	Total engagement with +ve Comments
-0.965	5	13	0.965	18	40
-0.964	10	11	0.964	21	69
-0.963	16	48	0.963	64	139
-0.962	7	8	0.962	15	11
-0.961	33	235	0.961	268	26
-0.960	2	23	0.960	25	29
-0.960	18	28	0.960	46	41
-0.959	3	9	0.959	12	19
-0.959	9	33	0.959	42	14
-0.959	4	43	0.959	47	2
-0.956	1	21	0.956	22	133
-0.954	3	11	0.954	14	25
-0.953	4	14	0.953	18	44
-0.953	3	15	0.953	18	26
-0.952	31	268	0.952	299	102
-0.951	3	13	0.951	16	25
-0.950	3	9	0.950	12	314
-0.949	17	21	0.949	38	21
-0.947	8	49	0.947	57	69
-0.943	0	9	0.943	9	94
-0.943	8	28	0.943	36	34
-0.941	17	14	0.941	31	13
-0.941	12	17	0.941	29	57
-0.940	8	46	0.940	54	118
-0.939	0	1	0.939	1	85
-0.937	2	50	0.937	52	24
-0.932	33	39	0.932	72	9
-0.931	4	6	0.931	10	77
-0.929	17	34	0.929	51	13
-0.928	17	62	0.928	79	106
-0.927	0	17	0.927	17	5
-0.926	8	11	0.926	19	232
-0.924	3	21	0.924	24	54
-0.923	0	25	0.923	25	130
-0.923	3	5	0.923	8	86
-0.923	10	15	0.923	25	62
-0.922	20	141	0.922	161	21
-0.922	61	293	0.922	354	269
-0.921	3	27	0.921	30	24
-0.920	3	6	0.920	9	225

Sentiment Score	comment replies count	total reactions count	Absolute Sentiment	Total engagement with -ve Comments	Total engagement with +ve Comments
-0.917	13	42	0.917	55	84
-0.916	5	34	0.916	39	82
-0.915	36	15	0.915	51	4
-0.915	4	30	0.915	34	4
-0.912	9	46	0.912	55	42
-0.912	2	26	0.912	28	14
-0.911	3	20	0.911	23	202
-0.911	4	31	0.911	35	110
-0.909	1	12	0.909	13	13
-0.904	3	29	0.904	32	318
-0.904	6	16	0.904	22	28
-0.903	5	33	0.903	38	491
-0.903	0	7	0.903	7	32
-0.903	6	5	0.903	11	59
-0.903	8	24	0.903	32	10
-0.902	4	14	0.902	18	96
-0.897	20	54	0.897	74	9
-0.897	3	8	0.897	11	69
-0.897	6	53	0.897	59	21
-0.896	1	6	0.896	7	20
-0.893	1	8	0.893	9	243
-0.893	4	3	0.893	7	22
-0.892	5	11	0.892	16	93
-0.890	0	4	0.890	4	25
-0.890	2	9	0.890	11	41
-0.890	16	22	0.890	38	80
-0.888	21	42	0.888	63	67
-0.888	2	2	0.888	4	35
-0.886	3	12	0.886	15	113
-0.886	6	41	0.886	47	9
-0.885	17	74	0.885	91	28
-0.884	13	34	0.884	47	43
-0.882	4	26	0.882	30	98
-0.882	4	8	0.882	12	23
-0.880	2	8	0.880	10	19
-0.879	1	82	0.879	83	66
-0.878	22	25	0.878	47	49
-0.876	13	17	0.876	30	33
-0.874	5	6	0.874	11	51
-0.872	1	4	0.872	5	16

Sentiment Score	comment replies count	total reactions count	Absolute Sentiment	Total engagement with -ve Comments	Total engagement with +ve Comments
-0.868	7	6	0.868	13	26
-0.867	0	5	0.867	5	27
-0.867	0	8	0.867	8	24
-0.866	0	3	0.866	3	306
-0.866	11	32	0.866	43	29
-0.865	5	12	0.865	17	8
-0.865	7	21	0.865	28	91
-0.864	4	10	0.864	14	46
-0.863	10	34	0.863	44	255
-0.860	0	12	0.860	12	139
-0.858	6	27	0.858	33	32
-0.857	8	32	0.857	40	90
-0.856	1	14	0.856	15	17
-0.855	7	14	0.855	21	8
-0.854	29	9	0.854	38	7
-0.854	6	7	0.854	13	62
-0.854	1	3	0.854	4	74
-0.853	2	17	0.853	19	58
-0.850	9	13	0.850	22	24
-0.848	0	9	0.848	9	83
-0.847	9	18	0.847	27	27
-0.846	5	11	0.846	16	22
-0.842	9	25	0.842	34	9
-0.842	1	6	0.842	7	26
-0.842	8	230	0.842	238	54
-0.842	1	8	0.842	9	17
-0.842	0	10	0.842	10	29
-0.841	1	4	0.841	5	61
-0.841	8	33	0.841	41	43
-0.840	1	20	0.840	21	111
-0.839	2	7	0.839	9	109
-0.836	1	11	0.836	12	24
-0.835	20	15	0.835	35	83
-0.834	9	13	0.834	22	30
-0.832	10	61	0.832	71	33
-0.832	17	67	0.832	84	445
-0.831	6	12	0.831	18	628
-0.828	6	35	0.828	41	46
-0.825	44	108	0.825	152	10
-0.823	7	31	0.823	38	96

Sentiment Score	comment replies count	total reactions count	Absolute Sentiment	Total engagement with -ve Comments	Total engagement with +ve Comments
-0.823	5	59	0.823	64	238
-0.819	4	22	0.819	26	3
-0.817	6	13	0.817	19	36
-0.817	7	9	0.817	16	39
-0.817	3	22	0.817	25	150
-0.816	3	6	0.816	9	60
-0.816	1	9	0.816	10	228
-0.815	11	36	0.815	47	90
-0.814	2	5	0.814	7	39
-0.814	3	15	0.814	18	29
-0.813	0	2	0.813	2	8
-0.812	6	42	0.812	48	245
-0.810	0	2	0.810	2	58
-0.809	1	14	0.809	15	14
-0.809	9	72	0.809	81	447
-0.805	0	3	0.805	3	10
-0.798	24	37	0.798	61	25
-0.798	2	103	0.798	105	34
-0.797	6	16	0.797	22	6
-0.797	4	22	0.797	26	38
-0.797	9	24	0.797	33	85
-0.794	21	42	0.794	63	9
-0.792	3	20	0.792	23	30
-0.786	43	30	0.786	73	28
-0.786	3	11	0.786	14	22
-0.784	3	17	0.784	20	123
-0.775	0	11	0.775	11	124
-0.775	2	15	0.775	17	19
-0.773	19	71	0.773	90	37
-0.772	8	38	0.772	46	158
-0.772	20	67	0.772	87	165
-0.772	18	41	0.772	59	173
-0.771	4	56	0.771	60	46
-0.770	22	53	0.770	75	63
-0.769	26	40	0.769	66	130
-0.768	9	19	0.768	28	110
-0.764	4	7	0.764	11	233
-0.760	1	15	0.760	16	476
-0.757	0	19	0.757	19	13
-0.756	1	6	0.756	7	73

Sentiment Score	comment replies count	total reactions count	Absolute Sentiment	Total engagement with -ve Comments	Total engagement with +ve Comments
-0.752	18	82	0.752	100	60
-0.752	88	270	0.752	358	125
-0.751	8	34	0.751	42	7
-0.751	2	42	0.751	44	25
-0.749	1	15	0.749	16	11
-0.749	3	9	0.749	12	7
-0.748	7	4	0.748	11	103
-0.745	8	7	0.745	15	102
-0.742	5	27	0.742	32	53
-0.740	39	36	0.740	75	38
-0.736	3	38	0.736	41	74
-0.735	16	34	0.735	50	17
-0.733	16	24	0.733	40	76
-0.732	8	14	0.732	22	18
-0.731	1	16	0.731	17	
-0.731	0	6	0.731	6	
-0.730	28	160	0.730	188	
-0.730	0	11	0.730	11	
-0.729	12	55	0.729	67	
-0.728	4	16	0.728	20	
-0.728	39	227	0.728	266	
-0.726	4	10	0.726	14	
-0.722	5	16	0.722	21	
-0.720	2	2	0.720	4	
-0.716	12	36	0.716	48	
-0.716	7	20	0.716	27	
-0.715	0	20	0.715	20	
-0.712	2	9	0.712	11	
-0.709	4	13	0.709	17	
-0.709	1	3	0.709	4	
-0.708	22	68	0.708	90	
-0.708	3	30	0.708	33	
-0.707	50	130	0.707	180	
-0.707	5	15	0.707	20	
-0.706	1	16	0.706	17	
-0.706	9	23	0.706	32	
-0.703	4	14	0.703	18	
-0.702	0	4	0.702	4	
-0.701	36	74	0.701	110	
-0.700	9	118	0.700	127	

Sentiment Score	comment replies count	total reactions count	Absolute Sentiment	Total engagement with -ve Comments	Total engagement with +ve Comments
-0.695	4	11	0.695	15	
-0.693	2	19	0.693	21	
-0.690	1	9	0.690	10	
-0.689	2	7	0.689	9	
-0.688	10	111	0.688	121	
-0.688	6	31	0.688	37	
-0.687	60	240	0.687	300	
-0.687	12	84	0.687	96	
-0.687	9	18	0.687	27	
-0.687	38	112	0.687	150	
-0.687	2	31	0.687	33	
-0.686	6	33	0.686	39	
-0.685	1	7	0.685	8	
-0.685	0	11	0.685	11	
-0.683	35	210	0.683	245	
-0.679	8	19	0.679	27	
-0.678	19	23	0.678	42	
-0.676	5	40	0.676	45	
-0.676	0	13	0.676	13	
-0.673	1	9	0.673	10	
-0.672	3	139	0.672	142	
-0.669	8	44	0.669	52	
-0.669	1	6	0.669	7	
-0.667	12	28	0.667	40	
-0.664	13	76	0.664	89	
-0.663	5	43	0.663	48	
-0.661	7	18	0.661	25	
-0.661	3	30	0.661	33	
-0.661	6	30	0.661	36	
-0.661	11	13	0.661	24	
-0.659	1	23	0.659	24	
-0.656	4	33	0.656	37	
-0.655	5	17	0.655	22	
-0.654	15	48	0.654	63	
-0.654	8	77	0.654	85	
-0.653	1	50	0.653	51	
-0.652	16	79	0.652	95	
-0.651	24	67	0.651	91	
-0.651	3	13	0.651	16	
-0.651	0	19	0.651	19	

Sentiment Score	comment replies count	total reactions count	Absolute Sentiment	Total engagement with -ve Comments	Total engagement with +ve Comments
-0.645	1	3	0.645	4	
-0.644	6	20	0.644	26	
-0.640	2	9	0.640	11	
-0.639	13	6	0.639	19	
-0.636	14	59	0.636	73	
-0.636	7	14	0.636	21	
-0.635	1	16	0.635	17	
-0.631	27	89	0.631	116	
-0.628	3	31	0.628	34	
-0.627	8	37	0.627	45	
-0.627	7	40	0.627	47	
-0.623	3	53	0.623	56	
-0.620	3	64	0.620	67	
-0.618	2	26	0.618	28	
-0.614	5	14	0.614	19	
-0.607	50	17	0.607	67	
-0.601	6	19	0.601	25	
-0.596	1	8	0.596	9	
-0.593	13	6	0.593	19	
-0.592	0	4	0.592	4	
-0.591	17	31	0.591	48	
-0.586	5	14	0.586	19	
-0.573	0	10	0.573	10	
-0.570	55	171	0.570	226	
-0.568	2	17	0.568	19	
-0.566	5	30	0.566	35	
-0.564	79	33	0.564	112	
-0.562	10	66	0.562	76	
-0.561	8	26	0.561	34	
-0.557	0	16	0.557	16	
-0.553	6	84	0.553	90	
-0.552	12	36	0.552	48	
-0.550	7	32	0.550	39	
-0.549	0	7	0.549	7	
-0.548	1	8	0.548	9	
-0.547	2	17	0.547	19	
-0.547	1	17	0.547	18	
-0.544	5	21	0.544	26	
-0.544	27	72	0.544	99	
-0.544	4	5	0.544	9	

Sentiment Score	comment replies count	total reactions count	Absolute Sentiment	Total engagement with -ve Comments	Total engagement with +ve Comments
-0.544	16	37	0.544	53	
-0.540	23	11	0.540	34	
-0.539	5	25	0.539	30	
-0.538	10	35	0.538	45	
-0.537	2	42	0.537	44	
-0.537	10	108	0.537	118	
-0.527	24	92	0.527	116	
-0.524	2	19	0.524	21	
-0.523	1	51	0.523	52	
-0.516	6	45	0.516	51	
-0.515	5	22	0.515	27	
-0.513	1	13	0.513	14	
-0.511	4	8	0.511	12	
-0.510	2	55	0.510	57	
-0.510	6	40	0.510	46	
-0.509	2	10	0.509	12	
-0.501	5	54	0.501	59	
-0.501	0	12	0.501	12	
0.503	46	42	0.503		
0.504	39	183	0.504		
0.522	5	12	0.522		
0.525	39	143	0.525		
0.537	4	4	0.537		
0.537	17	43	0.537		
0.539	38	113	0.539		
0.543	7	27	0.543		
0.543	0	1	0.543		
0.544	8	22	0.544		
0.550	4	14	0.550		
0.551	0	6	0.551		
0.552	39	100	0.552		
0.552	5	21	0.552		
0.552	29	142	0.552		
0.552	32	90	0.552		
0.552	14	44	0.552		
0.554	7	18	0.554		
0.556	33	55	0.556		
0.558	65	104	0.558		
0.561	2	6	0.561		
0.567	0	25	0.567		

Sentiment Score	comment replies count	total reactions count	Absolute Sentiment	Total engagement with -ve Comments	Total engagement with +ve Comments
0.569	13	50	0.569		
0.576	16	282	0.576		
0.580	3	22	0.580		
0.581	0	3	0.581		
0.587	18	23	0.587		
0.593	0	6	0.593		
0.598	2	55	0.598		
0.605	73	80	0.605		
0.608	3	11	0.608		
0.615	3	28	0.615		
0.623	0	5	0.623		
0.624	13	85	0.624		
0.629	0	13	0.629		
0.633	33	103	0.633		
0.636	10	41	0.636		
0.643	3	37	0.643		
0.646	10	59	0.646		
0.646	34	105	0.646		
0.649	1	10	0.649		
0.662	4	22	0.662		
0.663	16	13	0.663		
0.665	6	35	0.665		
0.666	7	12	0.666		
0.669	2	12	0.669		
0.670	0	2	0.670		
0.671	15	118	0.671		
0.675	9	16	0.675		
0.688	4	40	0.688		
0.694	3	23	0.694		
0.694	30	72	0.694		
0.696	3	22	0.696		
0.697	22	292	0.697		
0.699	5	16	0.699		
0.700	21	48	0.700		
0.704	12	82	0.704		
0.704	0	34	0.704		
0.705	2	11	0.705		
0.708	14	43	0.708		
0.717	23	95	0.717		
0.724	15	70	0.724		

Sentiment Score	comment replies count	total reactions count	Absolute Sentiment	Total engagement with -ve Comments	Total engagement with +ve Comments
0.725	1	23	0.725		
0.729	0	9	0.729		
0.732	13	64	0.732		
0.736	1	12	0.736		
0.740	45	61	0.740		
0.742	3	2	0.742		
0.745	22	210	0.745		
0.754	16	38	0.754		
0.759	0	130	0.759		
0.768	10	76	0.768		
0.773	1	61	0.773		
0.776	6	15	0.776		
0.777	84	185	0.777		
0.787	1	23	0.787		
0.789	14	211	0.789		
0.797	44	40	0.797		
0.800	15	67	0.800		
0.806	0	4	0.806		
0.812	0	4	0.812		
0.813	2	40	0.813		
0.814	0	14	0.814		
0.815	35	167	0.815		
0.815	3	107	0.815		
0.816	5	8	0.816		
0.817	95	223	0.817		
0.820	3	25	0.820		
0.824	64	427	0.824		
0.831	5	27	0.831		
0.835	23	36	0.835		
0.846	1	9	0.846		
0.850	29	67	0.850		
0.851	0	9	0.851		
0.856	3	66	0.856		
0.861	3	18	0.861		
0.864	3	17	0.864		
0.872	16	227	0.872		
0.874	5	17	0.874		
0.883	11	82	0.883		
0.887	0	25	0.887		
0.888	8	33	0.888		

Sentiment Score	comment replies count	total reactions count	Absolute Sentiment	Total engagement with -ve Comments	Total engagement with +ve Comments
0.894	11	69	0.894		
0.894	2	65	0.894		
0.899	3	32	0.899		
0.901	22	91	0.901		
0.901	1	8	0.901		
0.901	4	24	0.901		
0.906	7	36	0.906		
0.906	11	87	0.906		
0.906	6	17	0.906		
0.918	2	17	0.918		
0.924	6	60	0.924		
0.925	9	40	0.925		
0.929	2	31	0.929		
0.930	0	51	0.930		
0.938	3	13	0.938		
0.940	4	22	0.940		
0.940	5	22	0.940		
0.943	5	19	0.943		
0.943	49	257	0.943		
0.944	5	24	0.944		
0.946	5	3	0.946		
0.947	31	60	0.947		
0.947	7	39	0.947		
0.947	46	209	0.947		
0.948	21	118	0.948		
0.953	12	20	0.953		
0.953	31	59	0.953		
0.954	1	16	0.954		
0.956	1	7	0.956		
0.958	0	7	0.958		
0.962	5	57	0.962		
0.963	16	58	0.963		
0.968	4	54	0.968		
0.969	5	19	0.969		
0.973	14	69	0.973		
0.974	1	26	0.974		
0.974	6	16	0.974		
0.974	2	7	0.974		
0.974	1	25	0.974		
0.977	7	47	0.977		

Sentiment Score	comment replies count	total reactions count	Absolute Sentiment	Total engagement with -ve Comments	Total engagement with +ve Comments
0.977	5	12	0.977		
0.978	4	25	0.978		
0.979	2	59	0.979		
0.979	1	42	0.979		
0.979	15	96	0.979		
0.981	11	98	0.981		
0.981	3	21	0.981		
0.985	10	73	0.985		
0.985	1	29	0.985		
0.985	5	28	0.985		
0.986	25	420	0.986		
0.986	40	588	0.986		
0.986	0	46	0.986		
0.986	2	8	0.986		
0.986	14	82	0.986		
0.987	107	131	0.987		
0.987	0	3	0.987		
0.988	26	10	0.988		
0.989	8	31	0.989		
0.989	21	129	0.989		
0.990	12	48	0.990		
0.990	10	218	0.990		
0.990	10	80	0.990		
0.990	8	31	0.990		
0.991	5	24	0.991		
0.992	0	8	0.992		
0.992	80	165	0.992		
0.993	7	51	0.993		
0.993	2	12	0.993		
0.993	76	371	0.993		
0.993	0	10	0.993		
0.993	4	21	0.993		
0.993	2	32	0.993		
0.994	0	6	0.994		
0.994	3	35	0.994		
0.994	2	83	0.994		
0.995	0	9	0.995		
0.995	18	12	0.995		
0.995	2	26	0.995		
0.995	2	20	0.995		

Sentiment Score	comment replies count	total reactions count	Absolute Sentiment	Total engagement with -ve Comments	Total engagement with +ve Comments
0.995	14	109	0.995		
0.995	22	102	0.995		
0.995	1	18	0.995		
0.996	1	36	0.996		
0.996	12	146	0.996		
0.996	23	142	0.996		
0.996	11	162	0.996		
0.996	6	40	0.996		
0.996	7	56	0.996		
0.996	12	118	0.996		
0.996	7	103	0.996		
0.996	29	204	0.996		
0.996	36	440	0.996		
0.996	1	12	0.996		
0.996	8	65	0.996		
0.996	12	48	0.996		
0.996	11	114	0.996		
0.996	0	7	0.996		
0.996	3	22	0.996		
0.996	2	9	0.996		
0.996	0	7	0.996		
0.997	65	38	0.997		
0.997	8	94	0.997		
0.997	9	44	0.997		
0.997	8	30	0.997		
0.997	13	61	0.997		
0.998	5	12	0.998		
0.998	25	51	0.998		
0.998	4	14	0.998		

Appendix C: Statistical Output

XLSTAT 2022.4.1.1383 - Two-sample t-test and z-test - Start time: 01/08/2023 at 11:21:16 / End time: 01/08/2023 at 11:22:54 / Microsoft Excel 15.05501
Sample 1: Workbook = Taher's Data Regression.xlsm / Sheet = Sheet3 / Range = 'Sheet3'!$F$1:$F$336 / 335 rows and 1 column
Sample 2: Workbook = Taher's Data Regression.xlsm / Sheet = Sheet3 / Range = Sheet3!$G$1:$G$212 / 211 rows and 1 column
Hypothesized difference (D): 0
Significance level (%): 5
Population variances for the t-test: Assume equality

Summary statistics:

Variable	Observations	Minimum	Maximum	Mean	Std. deviation
Total engagement with -ve Comments	335	1.000	358.000	42.9	53.066
Total engagement with +ve Comments	211	1.000	628.000	77.3	94.596

Normality test:

Shapiro-Wilk test (Total engagement with -ve Comments):

W	0.631
p-value (Two-tailed)	**<0.0001**
alpha	0.05

Test interpretation:
H0: The residuals follow a Normal distribution.
Ha: The residuals do not follow a Normal distribution.
As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.

Shapiro-Wilk test (Total engagement with +ve Comments):

W	0.697
p-value (Two-tailed)	**<0.0001**
alpha	0.05

Test interpretation:
H0: The residuals follow a Normal distribution.
Ha: The residuals do not follow a Normal distribution.
As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.

t-test for two independent samples / Two-tailed test:

95% confidence interval on the difference between the means:
[-46.847, -21.988]

Difference	-34.417
t (Observed value)	-5.439
|t| (Critical value)	1.964
DF	544
p-value (Two-tailed)	**<0.0001**
alpha	0.05

Test interpretation:
H0: The difference between the means is equal to 0.
Ha: The difference between the means is different from 0.
As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.

XLSTAT 2022.4.1.1383 - Linear regression - Start time: 01/08/2023 at 10:15:32 / End time: 01/08/2023 at 10:15:34
Y / Dependent variables: Workbook = Taher's Data Regression.xlsm / Sheet = Sheet3 / Range = 'Sheet3'!$F:$F / 546 rows and 1 column
X / Quantitative: Workbook = Taher's Data Regression.xlsm / Sheet = Sheet3 / Range = 'Sheet3'!$E:$E / 546 rows and 1 column
Fixed Intercept: -1
Confidence interval (%): 95

Summary statistics:

Variable	Observations	Obs. with missing data	Obs. without missing data	Minimum	Maximum	Mean	Std. deviation
Total engagement	546	0	546	1.000	628.000	56.277	73.859
Absolute Sentiment	546	0	546	0.501	0.999	0.807	0.151

Correlation matrix:

	Absolute Sentiment	Total engagement
Absolute Sentiment	**1**	0.000
Total engagement	0.000	**1**

Regression of variable Total engagement:

Goodness of fit statistics (Total engagement):

Observations	546
Sum of weights	546
DF	545
R^2	0.370
Adjusted R^2	0.369
MSE	5509.278
RMSE	74.225
MAPE	242.576
DW	1.844
Cp	1.000

AIC	4704.346
SBC	4708.649
PC	0.633

Analysis of variance (Total engagement):

Source	DF	Sum of squares	Mean squares	F	Pr > F	p-values signification codes
Model	1.000	1761712.305	1761712.305	319.772	**<0.0001**	***
Error	545.000	3002556.695	5509.278			
Corrected Total	546.000	4764269.000				

Computed against model Y=Mean(Y)

*Signification codes: 0 < *** < 0.001 < ** < 0.01 < * < 0.05 < . < 0.1 < ° < 1*

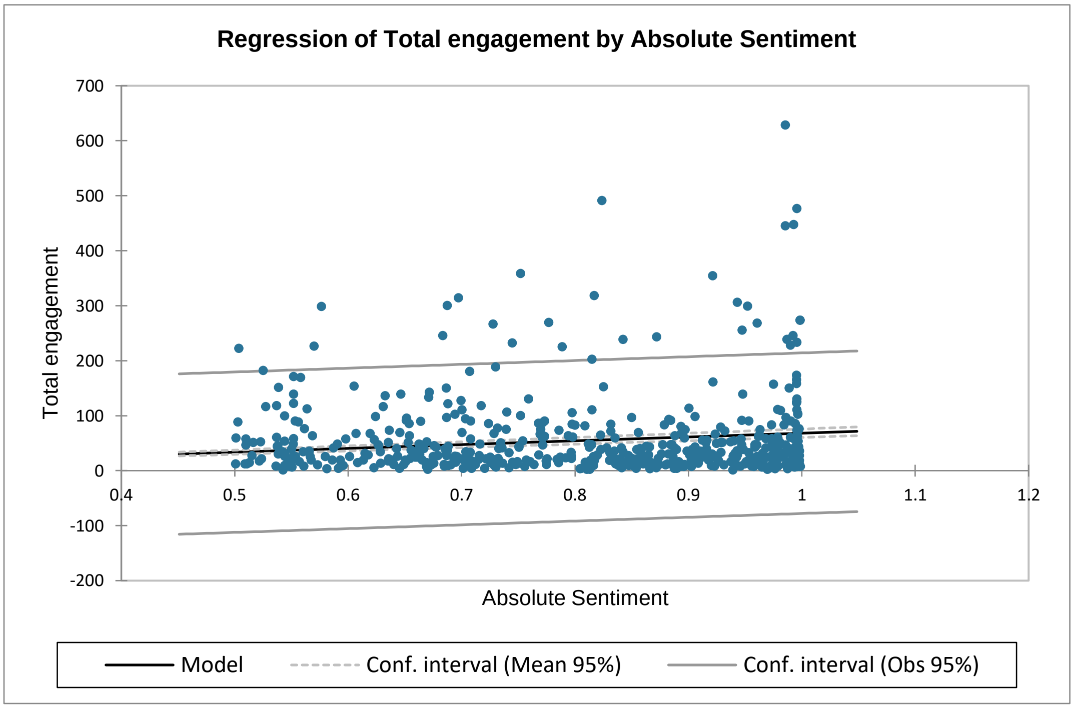
Model parameters (Total engagement):

Source	Value	Standard error	t	Pr > |t|	Lower bound (95%)	Upper bound (95%)
Intercept	-1.000					
Absolute Sentiment	69.161	3.868	17.882	**<0.0001**	61.564	76.758

*Signification codes: 0 < *** < 0.001 < ** < 0.01 < * < 0.05 < . < 0.1 < ° < 1*

Equation of the model (Total engagement):

Total engagement = -1+69.1609602818723*Absolute Sentiment



Interpretation (Total engagement):

Given the R2, 37% of the variability of the dependent variable Total engagement is explained by the explanatory variable.

XLSTAT 2021.1.1.1093 - Linear regression - Start time: 12/14/2021 at 19:54:05 / End time: 12/14/2021 at 19:54:06 / Microsoft Excel 15.05397
These results have been generated using XLSTAT Free. You can benefit from many more tools and options with a full version.
Y / Dependent variables: Workbook = Taher's Data Regression.xlsm / Sheet = Positive sentiments / Range = 'Positive sentiments'!$E:$E / 211 rows and 1 column
X / Quantitative: Workbook = Taher's Data Regression.xlsm / Sheet = Positive sentiments / Range = 'Positive sentiments'!$B:$B / 211 rows and 1 column
Fixed Intercept: -1
Confidence interval (%): 95
Tolerance: 0.0001

Summary statistics:

Variable	Observations	Obs. with missing data	Obs. without missing data	Minimum	Maximum	Mean	Std. deviation
Total Engagement	211	0	211	1.000	628.000	77.393	94.596
Positive Sentiment	211	0	211	0.503	0.998	0.836	0.163

Correlation matrix:

	Positive Sentiment	Total Engagement
Positive Sentiment	**1**	0.000
Total Engagement	0.000	**1**

Regression of variable Total Engagement:

Goodness of fit statistics (Total Engagement):

Observations	211
Sum of weights	211
DF	210
R^2	0.403
Adjusted R^2	0.400
MSE	9025.82
RMSE	95.004
MAPE	271.299
DW	1.941
Cp	1.000
AIC	1922.75
SBC	1926.10
PC	0.603

Analysis of variance (Total Engagement):

Source	DF	Sum of squares	Mean squares	F	Pr > F
Model	1	1280435.34	1280435.34	141.863	**<0.0001**
Error	210	1895423.65	9025.83		
Corrected Total	211	3175859.00			

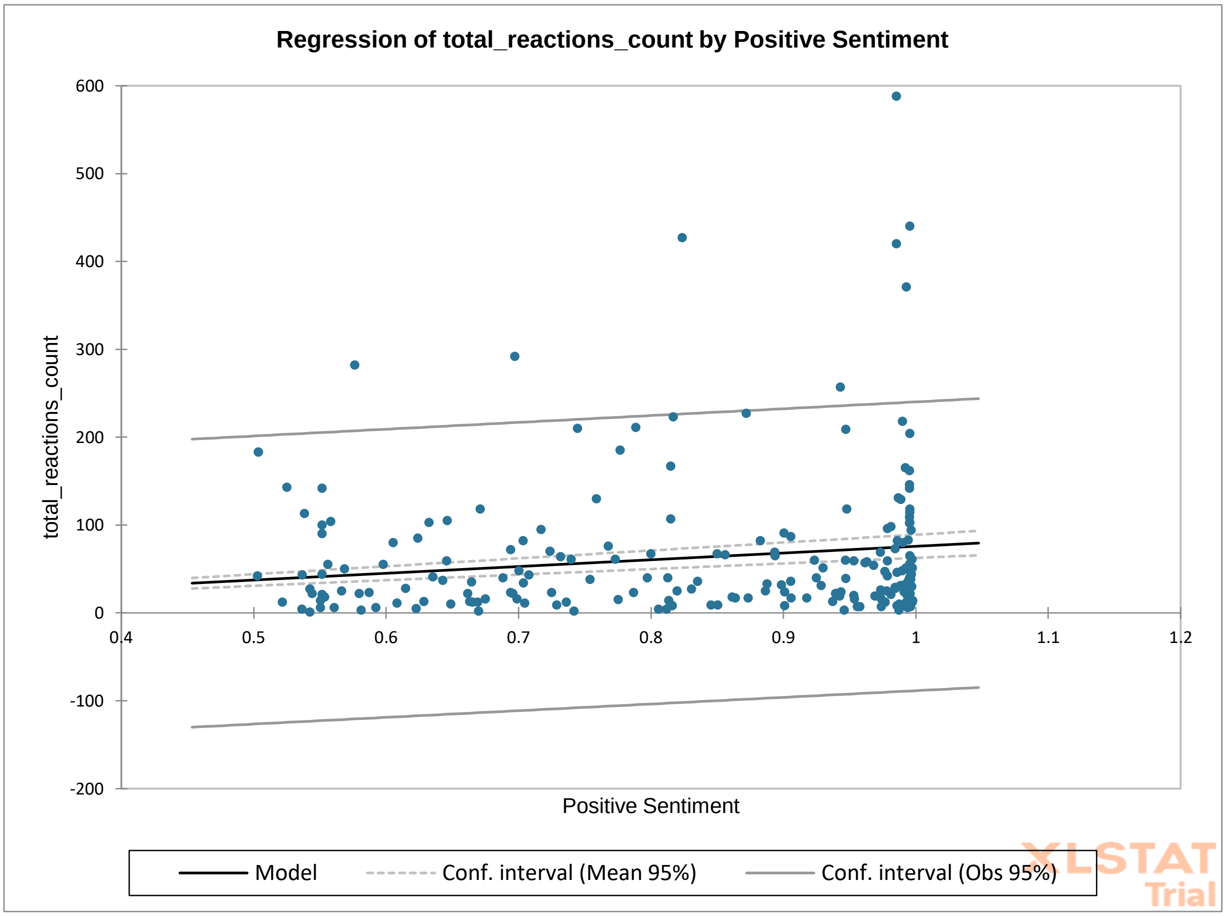
Computed against model Y=-1

Model parameters (Total Engagement):

Source	Value	Standard error	t	Pr > |t|	Lower bound (95%)	Upper bound (95%)
Intercept	-1.000					
Positive Sentiment	91.487	7.681	11.911	**<0.0001**	76.345	106.628

Equation of the model (Total Engagement):

Total Engagement = -1+91.4865255312304*Positive Sentiment



Interpretation (Total Engagement):

Given the R2, 40% of the variability of the dependent variable Total Engagement is explained by the explanatory variable.

XLSTAT 2021.1.1.1093 - Linear regression - Start time: 12/04/2021 at 22:18:02 / End time: 12/04/2021 at 22:18:05 / Microsoft Excel 15.05397
These results have been generated using XLSTAT Free. You can benefit from many more tools and options with a full version.
Y / Dependent variables: Workbook = Taher's Data (2).xlsx / Sheet = Negative Sentiments / Range = 'Negative Sentiments'!$E:$E / 335 rows and 1 column
X / Quantitative: Workbook = Taher's Data (2).xlsx / Sheet = Negative Sentiments / Range = 'Negative Sentiments'!$B:$B / 335 rows and 1 column
Fixed Intercept: -1
Confidence interval (%): 95
Tolerance: 0.0001

Summary statistics:

Variable	Observations	Obs. with missing data	Obs. without missing data	Minimum	Maximum	Mean	Std. deviation
Total Engagement	335	0	335	1.000	358.000	42.976	53.066
Negative Sentiment	335	0	335	-0.999	-0.501	-0.789	0.141

Correlation matrix:

	Negative Sentiment	Total Engagement
Negative Sentiment	**1**	0.000
Total Engagement	0.000	**1**

Regression of variable Total Engagement:

Goodness of fit statistics (Total Engagement):

Observations	335
Sum of weights	335
DF	334
R^2	0.385
Adjusted R^2	0.383
MSE	2924.273
RMSE	54.077
MAPE	197.139
DW	1.896
Cp	1.000
AIC	2674.567
SBC	2678.381
PC	0.619

Analysis of variance (Total Engagement):

Source	DF	Sum of squares	Mean squares	F	Pr > F
Model	1	611702.871	611702.871	209.181	**<0.0001**
Error	334	976707.129	2924.273		
Corrected Total	335	1588410.000			

Computed against model Y=-1

Model parameters (Total Engagement):

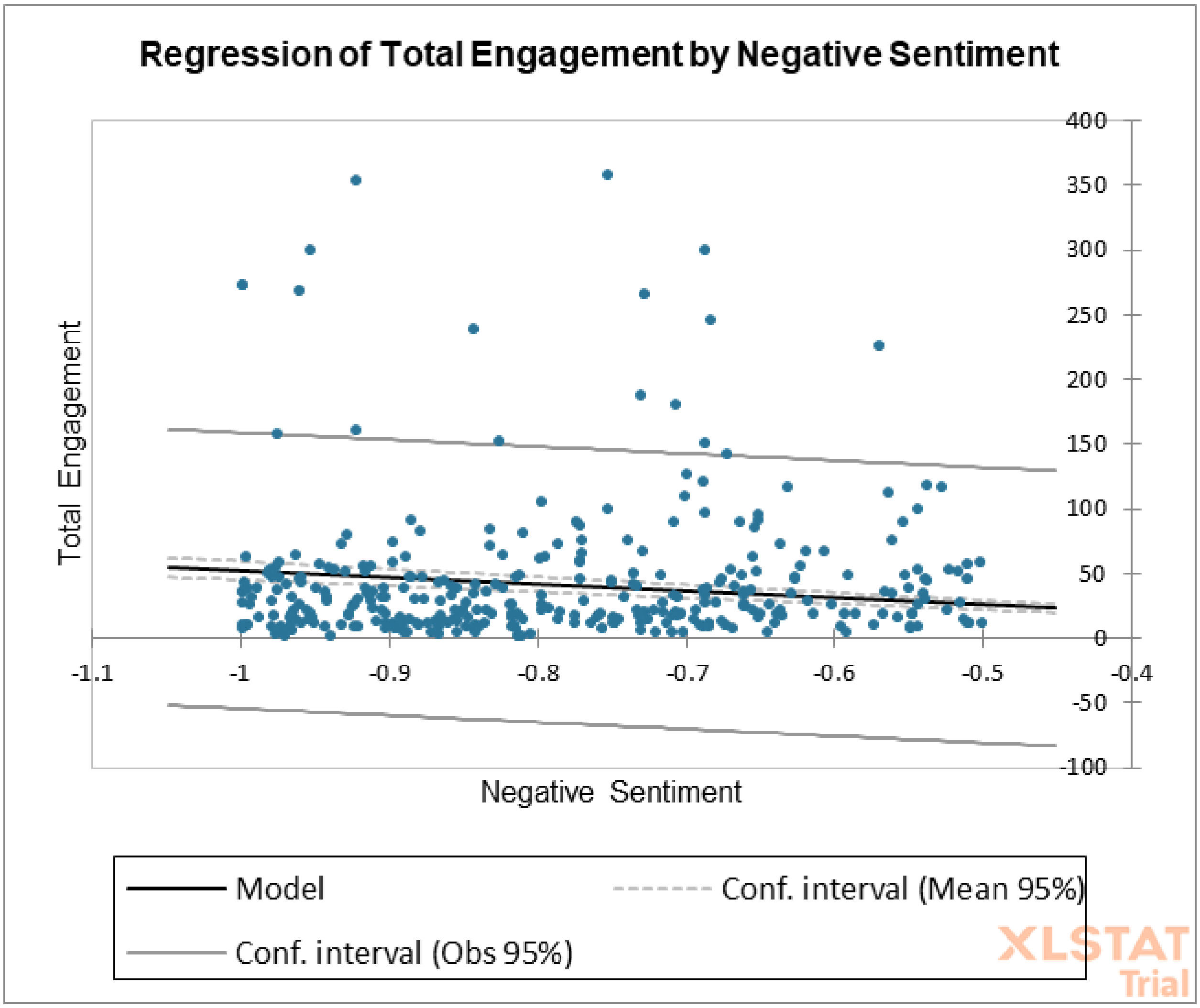
Source	Value	Standard error	t	Pr > |t|	Lower bound (95%)	Upper bound (95%)
Intercept	-1.000					
Negative Sentiment	-53.299	3.685	-14.463	**<0.0001**	-60.548	-46.050

Equation of the model (Total Engagement):

Total Engagement = -1-53.2993069519679*Negative Sentiment

Interpretation (Total Engagement):

Given the R2, 39% of the variability of the dependent variable Total Engagement is explained by the explanatory variable.



XLSTAT 2021.1.1.1093 - Linear regression - Start time: 12/04/2021 at 21:54:38 / End time: 12/04/2021 at 21:54:40 / Microsoft Excel 15.05397
Y / Dependent variables: Workbook = Taher's Data (2).xlsx / Sheet = Negative Sentiments / Range = 'Negative Sentiments'!$D:$D / 335 rows and 1 column
X / Quantitative: Workbook = Taher's Data (2).xlsx / Sheet = Negative Sentiments / Range = 'Negative Sentiments'!$B:$B / 335 rows and 1 column
Fixed Intercept: -1
Confidence interval (%): 95
Tolerance: 0.0001

Summary statistics:

Variable	Observations	Obs. with missing data	Obs. without missing data	Minimum	Maximum	Mean	Std. deviation
total_reactions_count	335	0	335	1.000	293.000	34.072	44.442
Negative Sentiment	335	0	335	-0.999	-0.501	-0.789	0.141

Correlation matrix:

	Negative Sentiment	total_reactions_count
Negative Sentiment	**1**	0.000
total_reactions_count	0.000	**1**

Regression of variable total_reactions_count:

Goodness of fit statistics (total_reactions_count):

Observations	335
Sum of weights	335
DF	334
R^2	0.362
Adjusted R^2	0.360
MSE	2046.341
RMSE	45.237
MAPE	197.917
DW	1.877
Cp	1.000
AIC	2554.974
SBC	2558.789
PC	0.642

36.2% is explained

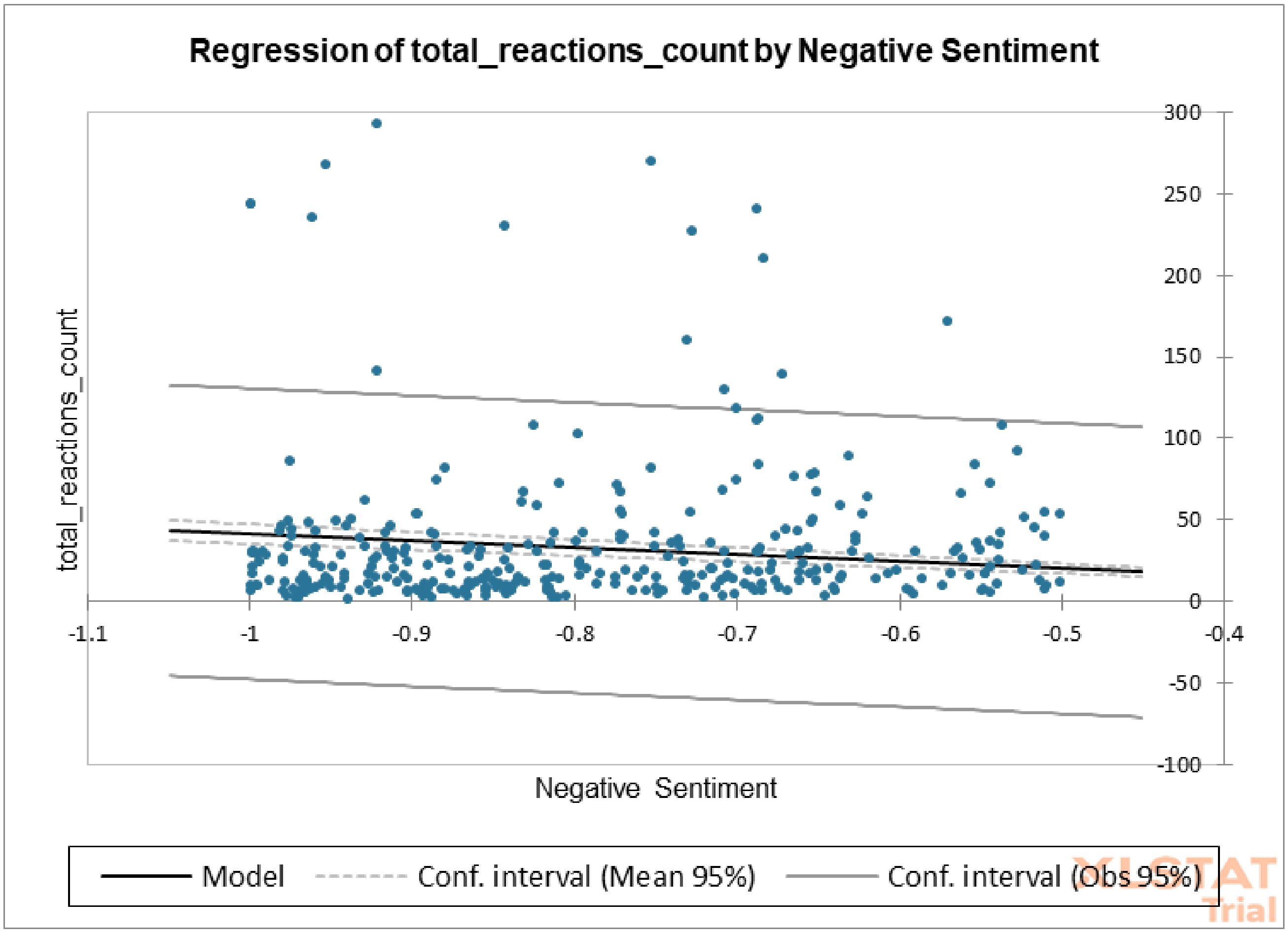
Analysis of variance (total_reactions_count):

Source	DF	Sum of squares	Mean squares	F	Pr > F
Model	1	388253.100	388253.100	189.730	**<0.0001**
Error	334	683477.900	2046.341		
Corrected Total	335	1071731.000			

Computed against model Y=-1

Model parameters (total_reactions_count):

Source	Value	Standard error	t	Pr > |t|	Lower bound (95%)	Upper bound (95%)
Intercept	-1.000					
Negative Sentiment		3.083	-13.774	**<0.0001**	-48.527	-36.399



Equation of the model (total_reactions_count):

total_reactions_count = -1-42.4628137563205*Negative Sentiment

y=a+bx

Interpretation (total_reactions_count):

Given the R2, 36% of the variability of the dependent variable total_reactions_count is explained by the explanatory variable.