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COVID-19 in the UK: sentiment and emotion analysis of Tweets over time.

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COVID-19 in the UK: Sentiment and Emotion Analysis of Tweets Over Time

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Abstract

We performed an analysis of tweets concerning the COVID-19 pandemic in the UK over a two-year period, selecting fifteen timelines. Over 110,000 tweets were obtained from Twitter and analysed using BERT and Text2Emotions for sentiment and emotion analysis, respectively. The most common emotions expressed on Twitter about COVID-19 in the UK appeared to be surprise and fear. This is not unusual, given the unprecedented nature of the pandemic. However, as time passed, there was a notable shift in sentiment towards other emotions, such as sadness and happiness. Moreover, more positive than negative sentiments were observed over the fifteen timelines studied: eight positive sentiments to seven negative ones. Further, results indicated that confirmed cases, deaths, and government policy heavily influenced public sentiment. This study sheds light on the collective state of mind surrounding the pandemic and provides insight into how people reacted emotionally over time to COVID-19. The results provide valuable insights for policymakers and other stakeholders looking to understand how people respond in times of crisis. Furthermore, it illustrates how sentiment analysis can be used effectively to gain deeper insights into public perception over time. As such, this study is a valuable contribution to understanding the human emotional response, demonstrating how sentiment and emotion can be used to better comprehend a situation and react accordingly.

Keywords: COVID-19, Sentiment Analysis, Emotion Analysis, Text2Emotion, BERT Model

1 Introduction

COVID-19, also known as the coronavirus, was first discovered in Wuhan, China, over two years ago [1]. Its effects were so devastating that the World Health Organisation declared it a public health emergency on January 30, 2020, barely a month after its discovery in December 2019 [2]. Within three months of its discovery, the virus had spread to almost 38 nations, causing chaos around the world and alarm and uncertainty among many [3, 4]. Hospitals were crowded at this time, and governments found it difficult to provide basic healthcare for their people. The COVID-19 virus was formally classified as a global pandemic by Dr Tedros Adhanom Ghebreyesus, Director-General of the World Health Organization, on March 11, 2020. One of the nations most severely affected by the virus was the United Kingdom, which as of September 2022 had over 23 million confirmed cases and more than 192,000 deaths [5].

1.1 The COVID-19 Pandemic in the UK

The COVID-19 pandemic has no doubt been one of the most devastating and disruptive events to happen to humanity in recent memory. No facet of life has been spared from the harsh effects of the pandemic. The outbreak has significantly impacted how people interact in all contexts, including work, school, travelling, and even social gatherings [6]. The UK was one of the European countries with the highest number of COVID-19 cases, with the first confirmed case being reported on January 31, 2020 [7]. Barely nine months later, in October 2020, the UK recorded over 400,000 confirmed cases of COVID-19 and over 42,000 deaths [5]. To combat the pandemic and mitigate its effects, the UK government put several measures in place, such as imposing lockdown restrictions, implementing social distancing guidelines, and using a contact tracing app. In a bid to stop the spread of the virus, the lockdown restrictions were announced in 2020 and lasted for a year [8]. These control measures have been met with much controversy from the citizens. Some argue that they are too restrictive and negatively impact mental health. Others, however, say that they are essential to stop the virus from spreading. As of November 2020, the virus had spread across 180 countries [9]. Since its discovery till this time, neither the UK nor most countries have developed a vaccine to combat the virus and prevent it from killing so many people. Following MHRA clearance, however, the United Kingdom allowed COVID-19 vaccine use in emergencies for the first time on December 2nd, 2020.

1.2 Benefits of Understanding People's Sentiment and Emotion of COVID-19 (During and Post-Covid)

As of July 2022, there were over 23 million confirmed cases and 180,000 deaths from the pandemic in the UK. Therefore, it is imperative to study the sentiments and emotions of UK citizens during the pandemic and consider their impact on people's lives. Carrying out a sentiment and emotion analysis is an effective way to study people's feelings and emotions during the pandemic. This analysis will help us discover and understand how people's sentiments and emotions evolved from the news of the first COVID-19 death in the UK to two years after that.

1.3 Emotional Analysis of Tweets

The outbreak of COVID-19 has resulted in a global health crisis. As the events of the outbreak unfolded, many people worldwide turned to social media as an avenue to share information and express their opinions about the outbreak [10]. Twitter is a social media site where users can communicate with one another by sharing brief messages known as "tweets." Twitter has become one of the most widely used social media platforms, with over 229 million daily active users worldwide [11]. Twitter serves as a platform for users to share their thoughts and feelings about current events as well as a source of real-time information about these events [12]. As of January 2022, there were an estimated 18.4 million Twitter users in the United Kingdom. This is a significant increase compared to the 13.7 million users reported in 2019. The vast majority of UK Twitter users are between 18 and 49, with nearly two-thirds falling into the 18-34 age bracket [13]. According to 2020 survey data, the UK has an active Twitter audience in addition to a massive number of users since roughly 87% of users aged 15 and over check in to their Twitter accounts at least once a week, and 59% use it every day [14]. This makes Twitter a valuable source of data for sentiment analysis.

In this paper, we will use sentiment and emotion analysis to critically analyse how the UK public has felt about the coronavirus over time through social media, specifically Twitter. Sentiment analysis, also known as opinion mining, is the use of natural language processing, text analysis, and computational linguistics to identify and extract subjective information from source materials. It can be used to determine the emotional tone of a piece of text, such as a social media post or a product review, and can be used in various applications such as marketing, customer service, and politics [15, 16]. Twitter is a popular microblogging site that allows users to share short messages, or "tweets", of up to 280 characters. Twitter has developed into a valuable data source for sentiment and emotion analysis in relation to the COVID-19 discourse due to its popularity and global reach. This paper used a dataset of over 118,000 tweets about COVID-19 in the UK, collected between March 2020 and January 2022. We will be using this dataset to examine how the sentiment and emotion of tweets about COVID-19 have changed over time, adopting the BERT model for sentiment analysis and the Text2Emotion for emotion analysis. The contribution of this paper is divided into seven folds.

- Extract tweets based on different incidents across various timelines of the pandemic.
- Examine the general sentiment about COVID-19 and people's perceptions.
- Explore the regularity of sentiment evolution by examining the tweets from (1).
- Identify and explore the evolution of people's emotions over time-based on the tweets.
- Analyse and compare emotions in the tweets captured for the time frames.
- Discuss the impact of government regulations and announcements on overall emotions.
- Make recommendations for further research.

Although research on the sentiment analysis of COVID-19 on people's emotions has been conducted, previous researchers have been unable to analyze tweets within the timelines following the lockdown. There were also a lot of studies that did not focus on a specific country. People's lives and the economies of countries, including the UK, are still being impacted by the COVID-19 pandemic. Although the number of reported deaths or confirmed cases has significantly decreased over time, the fight to eradicate the virus is far from over.

Therefore, the main objective of this research is to chronologically study and understand the sentiments and emotions of UK citizens on Twitter across different timelines from the first COVID-19 death until two years later. We expect that the sentiment and emotions of tweets about COVID-19 will change over time, in line with the changing situation of the pandemic. In the early stages of the outbreak, when information about the virus emerged, we expected to see a lot of fear and uncertainty. As the situation progresses and more information becomes available, we expect to see a decrease in negative sentiments and emotions as people become more accustomed to the idea of the virus and are better able to cope with it.

2 Literature Review

Since the inception of the COVID-19 pandemic, a lot of research has been done worldwide. This section looks into previous research efforts that have been made concerning the COVID-19 pandemic. It is crucial to conduct a critical analysis of earlier studies in order to show the originality of this research work. In their investigation of the emotions and psychology of Twitter users during the COVID-19 lockdown, Priyadarshini et al. [17] made the case that the rapid spread of the virus may have impacted people's psychology. The study also draws attention to the potential link between increased multimedia device use and psychological disorders due to government emergency protocols. The study conducts a sentiment analysis of Twitter data during the pandemic lockdown, covering only the second and fourth weeks after the lockdown was imposed. However, the study covers tweets from all over the world without considering that lockdowns were not imposed at the same time across the different regions. Although the study claims to have covered the whole world, it didn't consider people's sentiments before the lockdown.

During the COVID-19 pandemic, Mathur et al. [18] made an effort to research the feelings that Twitter users around the world were experiencing. The study's goal was to divide tweets into positive and negative categories before further subdividing them into the six fundamental emotions Ekman suggested: surprise, joy, sadness, anger, fear, and disgust [19]. Their findings indicate that the number of positive and negative tweets was nearly equal. The emotion classification reveals that a higher percentage of tweets are connected to trust, demonstrating that people were optimistic about fighting COVID-19 and the measures put in place by governments around the world. The majority of other tweets are filled with fear as COVID-19 cases continue to rise and spread quickly around the globe. At the time of the research, there was no effective vaccination, which could have accounted for the fear in the tweets. The research, however, did not show a discernible shift in people's emotions at particular timelines (for example, during the lockdown in various countries). Also, since government regulations would be different in various regions of the world, the research could have attempted to understand the emotions in each country based on their government regulations.

Dubey et al. [20] carried out a Twitter sentiment study for specific countries, including France, Germany, Belgium, Switzerland, Australia, China, India, and the United States of America, during the COVID-19 pandemic. The study takes the eight fundamental emotions—fear, pleasure, anticipation, anger, disgust, sorrow, surprise, and trust—into account. Most tweets about anger and anticipation come from France and Germany, respectively. While Switzerland has more tweets about fear, the United States reports the most tweets of disgust. The country with the highest percentage of joy was India, while Switzerland had the highest percentage of sadness. The majority of tweets that express surprise and trust come from Belgium. The shortcoming of this study is that it only summarizes the feelings rather than segmenting them into distinct timelines for each nation.

An infoveillance analysis showing the top concerns of tweeters during the COVID-19 pandemic was published by Abd-Alrazaq et al. in [21]. The study uncovered specific themes, such as the virus's origins, modes of transmission, effects on economies, societies, and people, as well as methods of prevention. The majority of the tweets had positive sentiments. The negative tweets focused on COVID-19-related mortality and a spike in racism. On average, tweets about economic loss were more common than tweets about travel restrictions and warnings. In this study, only the COVID-19 pandemic concerns were taken into consideration when the analysis was done, not the public's psychology after the lockdown.

In 2020, Dhar et al. [22] presented a study on the impact of COVID-19 on the psychology of more than 15,000 university students. Anxiety levels have been found to be correlated with stressors associated with epidemics. The effects of the pandemic on the economy, daily life, education, and social support are the main sources of stress. The psychological effects of the COVID-19 lockdown on law enforcement personnel were examined by Varalakshmi and Swetha [23]. The execution of the legislation resulted in a huge population adhering to the regulations and restrictions during emergency situations, as well as quarantining those infected with the disease. Amujo et al. [24] performed chronological sentiment analysis of UK-originated vaccine-related tweets. These studies had two drawbacks: they were restricted to a small population and neglected to account for how emotions change over time.

3 Methodology

According to Figure 1, the study focuses on sentiment analysis and emotion detection of tweets relating to COVID-19 over a predetermined timeline (limited to tweets in the English language posted from the UK). The timeline was chosen based on the announcement of different measures by the government to control the spread of the virus. BERT and Text2emotions were used for sentiment analysis and emotion analysis, respectively, to precisely analyze the sentiments and emotions expressed in tweets about COVID-19. BERT was selected for this study because it has consistently outperformed a number of established NLP techniques [25]. The majority of BERT-based text classification studies produced positive outcomes across a range of languages [26].

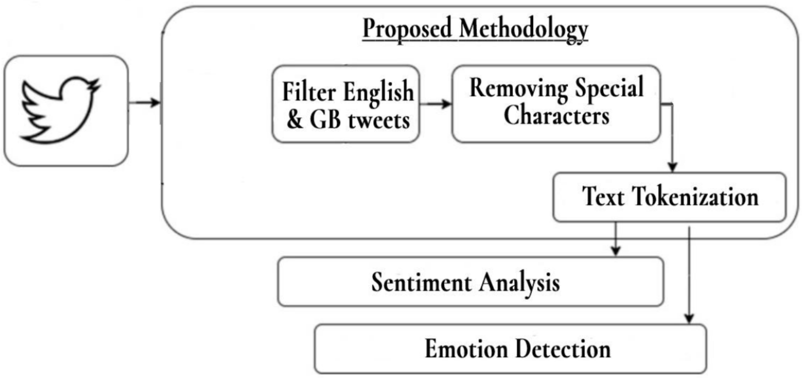


Fig. 1: The proposed methodology

Text2emotions is relatively fast, and the results are simple to comprehend. The same emotion classifier was also used in some earlier literature [20]. It begins by determining each word's grammatical function before identifying any adjectives and adverbs that may be present. The library then specifies the emotion connected to the word by comparing the adjectives with the pre-trained database. This section explains the methodology that was used in the study.

3.1 Data Collection

The application programming interface (API) for retrieving tweets on Twitter was used to extract the data. However, in order to access Twitter's API, a developer account is required. In order to ensure that the data obtained is used for legitimate or research purposes, Twitter validated the justifications for requesting an API key during this process. Tweets from the Twitter API were gathered using Tweepy, a Python library for extracting tweets from the Twitter API. This study uses fifteen timelines that are based on the crucial moments between the first COVID-19 death and two years later. The following keywords were used to extract tweets centred on this research: "Covid", "COVID19", "Covid-19", "COVID_19", "Coronavirus", "COVID19Pandamic", "Lockdown", "StayHome" and "StayHomeSaveLives". The first step is to collect data from Twitter. Several pieces of metadata were also retrieved, such as the time and date of creation and the tweet's text. As a result, no personally identifiable information was gathered. Table 1 below shows the timelines selected for this study.

Table 1: COVID-19 Event Timeline in the UK

S/N	Timeline	Date of Event
1	The first death from COVID-19 in the UK was confirmed.	5 March 2020
2	Government Advised self-isolation.	12 March 2020
3	The Prime Minister ordered all cafés, pubs, and restaurants to close.	20 March 2020
4	Death tolls reached 10,000 amidst the lockdown in the UK.	12 April 2020
5	Lockdown lifted, but social distancing advised.	13 May 2020
6	Health Secretary Matt Hancock announces hope for COVID vaccine.	13 June 2020
7	The majority of schools in the UK reopened.	1 September 2020
8	The UK reaches a million COVID-19 cases.	31 October 2020
9	The UK hits 50,000 COVID-related deaths.	11 November 2020
10	First COVID-19 Vaccine.	8 December 2020
11	COVID variants in the UK.	14 December 2020
12	Death toll reaches 100,000.	15 January 2021
13	A year since the UK recorded its first domestic cases of COVID-19.	30 January 2021
14	A third of UK adults are now fully vaccinated against COVID-19.	9 May 2021
15	Two years since the UK recorded its first domestic cases of COVID-19.	30 January 2022

3.2 Data Preparation

Texts derived from tweets are inherently noisy; cleaning the texts before further processing helps to produce higher quality and reduce computational complexity [27]. After extracting the tweets, we put the raw data through four preprocessing stages.

- Punctuation removal
- Blank space removal
- Removal of Twitter hashtags, usernames, retweets, Unicode characters, word lengthening, URLs, emoticons and internet shorthand/slang
- Text tokenization

3.3 Sentiment Detection using BERT

In order to understand how generally positive, negative, or neutral the tweets were, this phase entails analyzing the polarity of each tweet. BERT's model architecture (shown in Figure 2 consists of a multi-layer bidirectional transformer encoder, BERT, and a new language representation model that has achieved state-of-the-art performance on the majority of NLP tasks to which it has been applied (Hadjer 2021). It is pre-trained on a huge corpus of unlabeled text, which includes the entire English Wikipedia (2,500 million words) and the Book Corpus (800 million words). This process is used to train deep bidirectional representations from these texts in order to understand language context as best as possible. "Bidirectional" refers to the simultaneous consideration of both left and right contexts (previous and posterior tokens) in all layers [28].

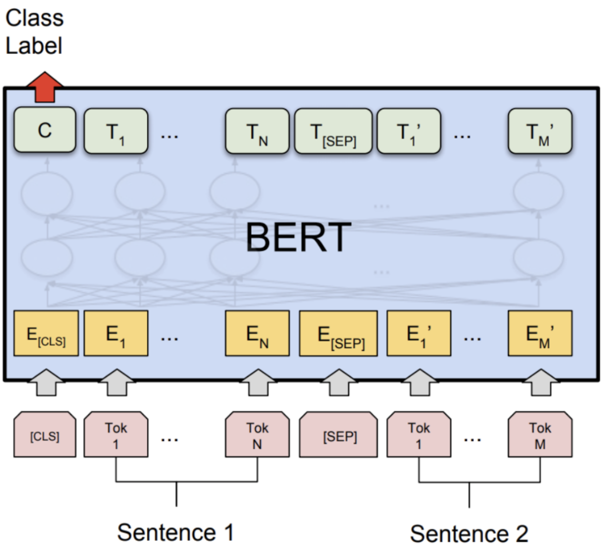


Fig. 2: The BERT Model architecture

3.4 Emotion Detection Using Text2Emotion

Text2Emotion is a Python package created to identify appropriate emotions embedded in text data [29]. Humans use their emotions appropriately when communicating and choose the right words to convey those emotions. Text2Emotion analyzes textual data for embedded emotions and generates an output dictionary. The top five emotion categories for tweets that are most effective are fear, sadness, anger, happiness, and surprise. The emotions are based on the fundamental emotions that leading studies on emotional theory have identified [30].

The user can access this data through a Python dictionary that has five keys for the five emotions that this program can identify. These values indicate how frequently each emotion appears in the text. The values of the emotions must be aggregated to a specific value, which must be either 1 or 0, with 0 only appearing in cases where no emotions were present in the text (such as for strings of characters that make no sense). So, for example, a passage of text that only expresses anger would have an "angry" value of 1 and a value of 0 for every other emotion.

4 Result

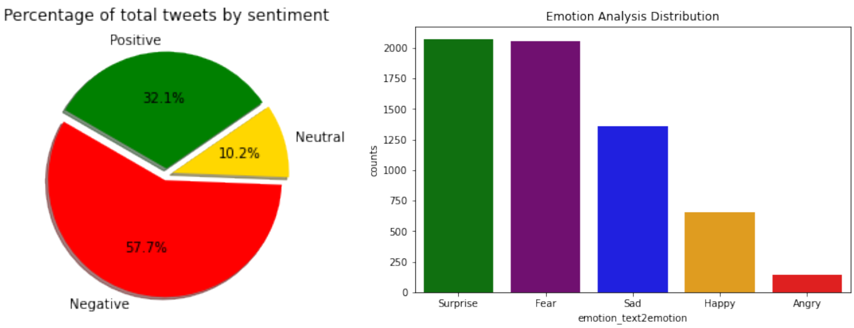
This section presents the findings of the analysis, discussed in terms of sentiments and emotions over time. Fear, sadness, and surprise were the most frequently expressed feelings in the tweets, which is understandable given the situation. Fear is a natural reaction to something potentially dangerous, sadness is often associated with loss, and surprise is an unexpected or astonishing event. Other emotions expressed included happiness and anger.

The results from each timeline are shown in the section below. The report represents the sentiments around COVID-19 in the UK. Stars represent the sentiment of a tweet, with 1 being the most negative and 5 being the most positive. In the following sections, we discussed the first five timelines and provide a summary of the sentiment polarity of the 15 timelines in the discussion section.

4.1 Timeline 1: The first death from COVID-19 in the UK was confirmed (5 March - 11 March 2020)

On 5th March 2020, the UK had its first COVID-19 death. The first death showed the magnitude of the threat COVID-19 poses to human lives, prompting a flood of negative tweets. Figure 3a shows that public opinion about the pandemic quickly turned negative after the first death was recorded. Negative sentiments, therefore, made up more than 57.7% (n = 3628) of all tweets, while neutral and positive sentiments made up 10.2% (n = 641) and 32.1% (n = 2017), respectively.

Figure 3b demonstrates that "surprise" and "fear," which together accounted for more than 60% of the emotions expressed in this timeline, were



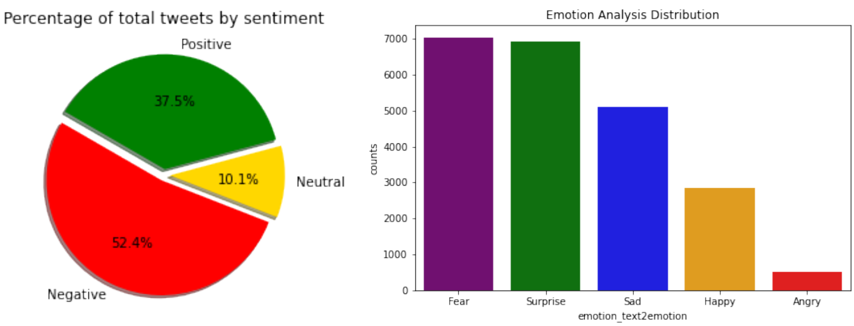
(a) Sentiment Polarity (b) Emotion Analysis

Fig. 3: Timeline 1 - Sentiment and Emotion Analysis

the most frequently expressed feelings. Given that there were more deaths during this time, this was to be expected. Due to the nature of the pandemic, the rate of spread, and the fatality rate, the predominant emotions of surprise, fear, and sadness were expected.

4.2 Timeline 2: Government Advised Self-isolation (12 March - 18 March 2020)

During this timeline, Prime Minister Boris Johnson confirmed that COVID-19 is not the festive flu, as many presumed, but a more lethal virus that can kill many people. Figures 4a shows that 52.4% (n = 11768) of people had negative sentiments toward self-isolation. 37.5% (n = 8427) had positive sentiments, while 10.1% (n = 2269) had neutral sentiments about the total tweet.



(a) Sentiment Polarity (b) Emotion Analysis

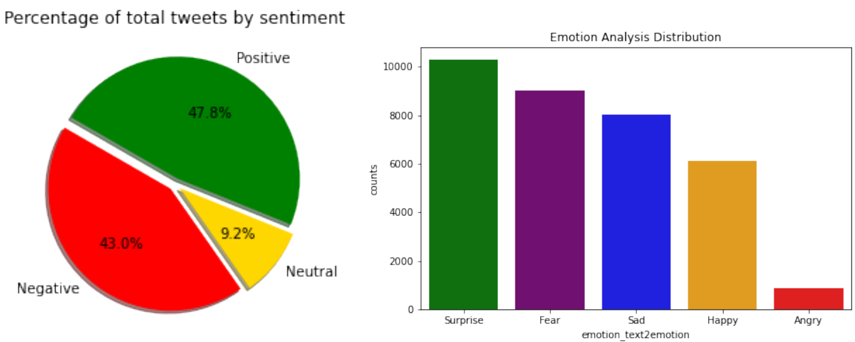
Fig. 4: Timeline 2 - Sentiment and Emotion Analysis

Figure 4b shows that 'surprise' and 'fear' were the most common responses of people to the imposed self-isolation. Although the sentiments for this timeline were a little bit more positive than the earlier timeline, there is a change in the dominant emotion from surprise to fear compared to Figure 3b.

4.3 Timeline 3: Prime Minister Orders All Cafés, Pubs, and Restaurants to Close (20 March - 26 March 2020)

During this timeline, Aberdeen FC players had a night out at a coronavirus hotspot just days before two players tested positive (Daily Record 2020). This period saw a huge increase in positive tweets as shown in Figure 5a. Here, we see that 47.8% (n = 16404) of tweets are positive, while 43.0% (n = 14765) and 9.2% (n = 3145) are negative and neutral, respectively. This increase may be due to people's concern about the spread of the virus, and hence, the close of the entertainment and leisure centres seems to be received more positively.

Compared to timeline 2, this timeline meant safety and benefit for some people, as the Nursing and Midwifery Council confirmed that over 5,600 former nurses have offered to help combat the virus's spread, which correlated with a rise in positive sentiments in this timeline. Also, we can see in Figure 5b that people became happier and less afraid.

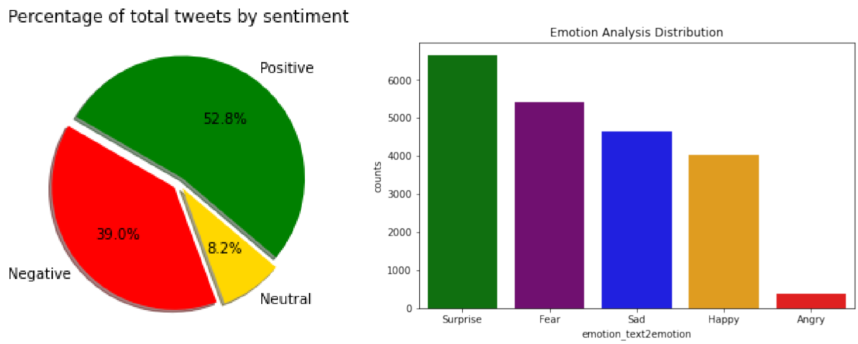


(a) Sentiment Polarity (b) Emotion Analysis

Fig. 5: Timeline 3 - Sentiment and Emotion Analysis

4.4 Timeline 4: Death Tolls Reached 10,000 Amidst the Lockdown in the UK (12 April - 18 April 2020)

Figure 6a shows that many tweets were positive amidst the sad news. This could be because of Capt. Tom Moore's NHS fundraiser. During Tom Moore's 100 laps of his garden, about a million people contributed to his JustGiving page, raising over £25 million for the NHS [31]. The percentage of positivity is 52.8% (n = 11166), the percentage of negativity is 39.0% (n = 8234), and the percentage of neutrality is 8.2% (n = 1736). As illustrated in Figure 6b, the high death toll amounted to 10,000 people during the lockdown. In an interview with BBC News, Health Secretary Matt Hancock stated that a decrease in the number of new cases and deaths all add to the effectiveness of the lockdown [32]. Here, we also see that the anger levels dropped.



(a) Sentiment Polarity

(b) Emotion Analysis

Fig. 6: Timeline 4 - Sentiment and Emotion Analysis

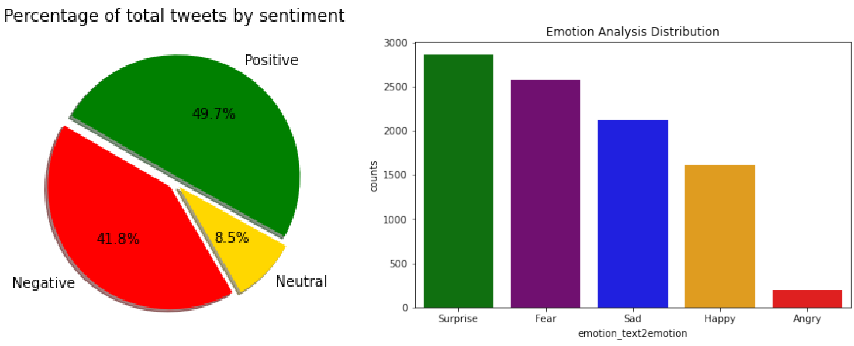
4.5 Timeline 5: Lockdown Lifted, But Social Distancing Advised (13 May - 19 May 2020)

During this timeline, Chancellor Rishi Sunak announced a recession in the UK economy. According to the data, 49.7% (n = 4658) of tweets were positive, 41.8% (n = 3912) were negative, and 8.5% (n = 796) were neutral. Positive tweets have decreased compared to timeline four because of the decline in the UK economy and the possibility of a noteworthy recession, as stated by Chancellor Rishi Sunak, Chancellor of the Exchequer.

9371 tweets were examined, and approximately 3000 tweets showed surprise at the lift in lockdown and recommendations on social distancing (see Figure 7b). We observed an increase in the level of fear in the UK community after the government scientists confirmed that the COVID-19 infection had progressed and could spread spontaneously.

5 Discussion

This study examined how the COVID-19 pandemic was perceived by UK citizens. It analysed tweets that were posted between the first case confirmed in the UK and two years after the initial case was reported. The data suggested a relationship between the various timelines and their impacts on the sentiment surrounding the timelines, including the emotions expressed towards an event



(a) Sentiment Polarity (b) Emotion Analysis

Fig. 7: Timeline 5 - Sentiment and Emotion Analysis

or governmental regulations. The sentiment of the tweets around particular timelines (events happening at specific times) and the evolution of emotions in the tweets were the two main sections we extracted from the 15 timelines of this study.

The sentiments surrounding each timeline showed slight variations, as shown in Table 2 below. The perspectives of the general public on COVID-19, governmental rules, and health-related information surrounding the timelines are reflected in these changes. The news about the first death from COVID-19 in the UK had a negative sentiment of 57.7%, only surpassed by the timeline 15: two years since the UK recorded its first domestic cases of COVID-19. In contrast, the positive sentiment was only 32% from the first timeline. This gradually increased as the government's efforts to stop the virus's spread by closing all cafés, bars, and restaurants grew more intense. People's sentiments appear to be positively influenced by governmental regulation and positive health information. On the other hand, a rise in negative sentiments resulted from the virus's spread and the development of COVID variants. Only a small portion of tweets in each timeline were neutral.

Then, we examined the emotions expressed in the tweets toward each timeline using the five primary emotions of surprise, fear, sadness, happiness, and anger. A bar chart was used to represent these emotions graphically.

In contrast to the time frame of the study by Priyadarshini et al. [17], the tweets analyzed in this study covered the period from March 5, 2020, to February 6, 2022, and they were only limited to the UK to obtain more streamlined results as opposed to the methodology used by Imran et al. [33]. According to the hypothesis previously stated in the literature review for this study, the emotions most commonly expressed at the beginning of the pandemic were surprise and fear, which gradually subsided post-pandemic.

According to the study's findings, we observed a consistent rise in the overall number of tweets extracted from the first timeline to the third timeline. The total number of tweets extracted decreased from the fourth to the seventh

Table 2: Overview of Sentiment in Each of the Timeline

S/N	Timeline	Negative	Neutral	Positive
1	The first death from COVID-19 in the UK was confirmed	3628 (57.7%)	641 (10.2%)	2017 (32.1%)
2	Government Advised self-isolation	11768 (52.4%)	2269 (10.1%)	8427 (37.5%)
3	Prime Minister orders all Cafés, pubs, and restaurants to close	14765 (43.0%)	3145 (9.2%)	16404 (47.8%)
4	Death tolls reached 10,000 amidst the lock-down in UK	8234 (39.0%)	1736 (8.2%)	11166 (52.8%)
5	Lockdown lifted, but social distancing advised	3912 (41.8%)	796 (8.5%)	4658 (49.7%)
6	Health Secretary Matt Hancock announces hope for COVID vaccine	1930 (42.1%)	403 (8.8%)	2253 (49.1%)
7	The majority of schools in the Uk reopened	885 (49.0%)	184 (10.2%)	738 (40.8%)
8	The UK reaches a million COVID-19 cases	2444 (53.5%)	337 (7.4%)	1787 (39.1%)
9	The UK hits 50,000 COVID-related deaths	1256 (45.0%)	220 (7.9%)	1316 (47.1%)
10	First COVID-19 Vaccine	807 (45.0%)	158 (8.8%)	830 (46.2%)
11	COVID variants in the UK	1746 (53.6%)	325 (10%)	1188 (36.5%)
12	Death tolls reach 100,000	1325 (42.5%)	302 (9.7%)	1491 (47.8%)
13	A year since the UK recorded its first domestic cases of COVID-19	1108 (43.9%)	218 (8.6%)	1197 (47.4%)
14	A third of UK adults are now fully vacci-nated against COVID-19	437 (47.3%)	73 (7.9%)	414 (44.8%)
15	Two years since the UK recorded its first domestic cases of COVID-19	191 (58.1%)	21 (6.4%)	117 (35.6%)

timeline. One thing to note is that there was a significant drop in tweets from timeline four to timeline five, totalling a difference of 11,765 tweets. At the eighth timeline, the number of tweets increased once more. This rise can be attributed to the increase in COVID-19 cases discovered during England's second lockdown on November 5, 2022. At timelines 9 and 10, the number of tweets started to decline. However, these timelines still showed a lot of positive sentiments. In addition, many tweets expressed surprise, fear, and sadness because the vaccine was known to have some side effects, while only a small number of people were happy about the development. When the COVID variants were found in the UK, many people began tweeting about it and expressing their emotions, primarily surprise and fear, with a lot of negative sentiment. As a result, more tweets were extracted at timeline 11. The number of tweets decreased from timeline 12 to timeline 15.

6 Conclusion

Online activity increased due to the global COVID-19 outbreak. People, including those in the UK, used social media platforms to share and receive information about the virus as well as to express their emotions. In order to understand how emotions have changed over time, we examined more than 100,000 tweets from the UK across 15 timelines for this study.

According to our findings, the most frequent emotions discussed in tweets about COVID-19, particularly in the early stages of the outbreak, were surprise and fear. As the pandemic spread, it became more common to see sad and happy emotions. This might be because lockdown procedures were successfully implemented in the UK and helped to contain the virus's spread. However, the decline in tweets indicated that people are likely less worried about the virus. It was also observed that positive sentiments increased steadily across the timelines. However, it is noteworthy that the 15th timeline, two years since the UK recorded its first domestic cases of COVID-19, had a negative sentiment of 58.1%.

Regardless of what the future holds, it is evident that governmental restrictions and policy modifications significantly impact people's emotions and how they express them on social media. Future research could expand the analysis to other languages and nations, as this study was only able to look at tweets in English and the United Kingdom. The use of irony and sarcasm in tweets, where the written literal meaning is frequently the opposite of the intended meaning, was also not taken into account in this study. Finally, there is the problem of nontext data in sentiment analysis. Emojis and other non-text data were not taken into account in the study. Despite these limitations, this study sheds light on how UK citizens have felt about COVID-19 over time. The findings can guide future policy choices and assist decision-makers in comprehending how their choices may affect people's emotions.

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