Emotion Shifts Analysis During Covid

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1 Introduction

The COVID-19 pandemic has brought a very strong impact to societies all around the world. It has altered day-to-day living, economies, healthcare systems, and many other facets of our society. Since the virus started spreading, a huge amount of information and opinion exchange began on social media. Twitter became a leading channel for people to express sentiment and share information with others for discussions regarding the pandemic and its related aspects. Understanding how public sentiment evolves during such a global crisis is crucial to policymakers, health professionals, and communicators. This would provide useful insights for them regarding the understanding of concerns and the way to effectively direct the behavior of the general public.

Though many studies have analyzed static snapshots of public sentiment towards COVID-19 [14, 21], there remains a gap in understanding the change in sentiment with respect to the different stages during the pandemic. Specifically, vaccine-related discussions have been popular due to their direct impingement on public health policies and vaccination uptake [20]. Analyzing sentiment dynamics over different stages of the pandemic can provide deeper insights into public opinion trends, which is beneficial to form strategies to combat misinformation and vaccine hesitancy.

In this study, we will explore the temporal changes in sentiment toward the COVID-19 vaccine by analyzing Twitter posts over distinct pandemic stages. These stages correspond to key events such as the initial outbreak, vaccine development announcements, authorization, rollout phases, and subsequent waves of infections. By segmenting the timeline, our aim is to identify the shifts in public sentiment corresponding to each significant event.

Also, different population groups may have different sentiment trends because of their very different experiences and roles during the pandemic. In this study, Twitter users are divided into five categories: healthcare personnel, media workers, organizations, scientists, and the general population. In this way, it is able to filter out sentiment trends specific to each group and observe how each group's view contributes toward the overall discussion [17].

Worth noticing, before group-level analysis, this study will first discuss the sentiments of certain individuals over time during the pandemic, as illustrated in Figure 1. We attempt to understand how individual-level sentiments shift over time by tracking selected users' Twitter messages over time. This longitudinal approach may provide a nuanced understanding of shifts in personal opinion that is hard to recognize from aggregated data. These insights are valuable during the development of effective communication strategies and interventions that aim to address the concerns of particular individuals or subgroups in society.

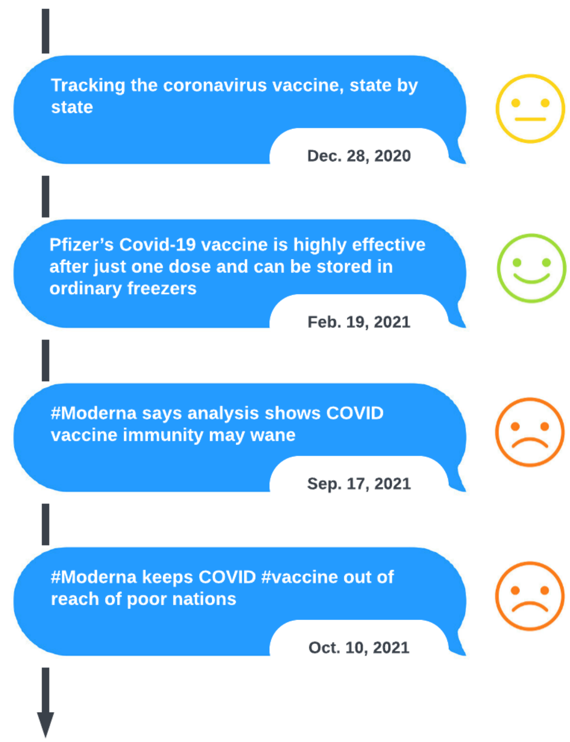

Figure 1: An case for sentiment shift at individual-level

Our approach addresses the following research questions:

- How do individual sentiments evolve over time, and what factors contribute to significant shifts in personal opinions?
- How has public sentiment toward the COVID-19 vaccine changed over the course of the pandemic?
- What specific sentiment patterns can be identified within different population groups regarding the vaccine?
- How do key events in the pandemic affect the dynamics of sentiments in these groups?

Studying these aspects is vital for several reasons. First, understanding sentiment evolution can help identify periods of increased public concern or misinformation spread, enabling timely interventions. Second, recognizing group-specific and individual sentiment patterns allows for tailored communication strategies that address the unique needs and concerns of each group and individual. Lastly,

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this research contributes to the broader field of computational social science by demonstrating how social media data can be leveraged to understand complex societal issues over time.

In the following sections, we will detail previous related work, our methodology for data collection and analysis and expected outcomes.

2 Related Work

2.1 Impact of COVID-19 on Different Cohorts

Due to differences in occupation, age and roles, the COVID-19 pandemic has affected various cohorts differently [10]. How their sentiments, perceptions, and behaviors have been influenced reveals similarities within cohorts and differences between them. For example, some front-line healthcare workers, who work directly with the positive COVID-19 cases, are obviously more vulnerable to physical infection and psychological breakdowns [8]. Another interesting example is schoolchildren. Although evidence suggests children and adolescents are less vulnerable to infection from COVID-19 [6] and some of them are even too young to understand the pandemic, their emotions are also impacted indirectly. These indirect factors include school closures, lack of outdoor activities, disrupted sleeping habits. Some teenagers' underlying mental illnesses may also have been triggered by this particular closure [12].

Recognizing these unique challenges and stressors faced by each cohort will help to propose targeted mental health interventions and support strategies. The analyses mentioned above are usually based on sociological experiments such as questionnaires or interviews. On this basis, we will conduct statistical analyses using large-scale data, hoping to provide a more rigorous theoretical basis for analysis.

2.2 Sentiment Analysis Techniques

Natural language processing (NLP) significantly helps sentiment analysis by mining the emotions behind textual content [13]. At the early stage, traditional approaches include lexicon-based methods and machine learning classifiers like Naive Bayes and Support Vector Machines (SVM). They highly rely on pre-defined dictionaries or features extracted from the text [16]. However, while easy to use, these early-stage sentiment analysis techniques sometimes fail to adapt to the constantly changing linguistic patterns, which are normally seen on platforms like Twitter or Facebook.

The neural networks, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), was widely recognized at the time of its invention as a major breakthrough in the field. They are good at identifying complex patterns in textual data and have significantly enhanced sentiment classification accuracy [23]. More recently, transformer-based models like Bidirectional Encoder Representations from Transformers (BERT) have achieved state-of-the-art results [5] at that time. These models pre-train deep bidirectional representations and then do fine-tune according to different tasks [19]. For example, Müller et al. [15] proposed COVID-Twitter-BERT (CT-BERT), which analyzed sentiments in social medias like Twitter during COVID-19. These previous researches provide solid techniques for our work to do fine-grained analysis.

2.3 Social Media Analysis During COVID-19

During the pandemic, social media plays a even more crucial role in the scenario of the world being locked up. Those media platforms, particularly Twitter, a microblogging and social networking platform launched in 2006, have been widely used to study public discourse and sentiment during the pandemic [4]. Researchers have analyzed Twitter data to monitor the spread of misinformation, gauge public sentiment toward health guidelines, and understand vaccine acceptance [11]. These studies highlight the role of social media as both a source of information and a reflection of public opinion. Some systems, like CrystalFeel [7], are specially designed for Twitter and is capable of predicting both the general intensity of emotions and sadness-specific intensity. CrystalFeel has supported works such as [14], which not only rating valence-arousal but also specifying different emotions including fear, anger, sadness, and joy.

Despite numerous studies focusing on sentiment analysis of social media data during the pandemic, there remains a gap in understanding temporal changes in sentiment in relation to key events. Most existing research provides snapshots of sentiment at specific points in time [1], lacking a longitudinal perspective that captures how sentiment evolves over different stages of the pandemic. Also, previous research mainly focus on overall sentiment across time, ignoring individual diversities. Our study aims to fill these gaps by analyzing sentiment dynamics over distinct pandemic stages for individuals. The enormous amount of data on Twitter makes this fine-grained analysis possible.

3 Methodology

In this section, we will describe our data collection and pre-processing, user categorization, and sentiment analysis methods.

3.1 Dataset

In this work, we aim to analyze sentiment changes through posts on Twitter. We adopted a dataset collected by Thushara Nair[1] which covers a long range from February 2020 to November 2021, with 228K tweets containing keywords or hashtags related to the COVID-19 vaccine. Each entry in the dataset contains not only the post data and tweet content but also the ID and profile of the user who posted it. This enables us to conduct end-to-end analysis without extensive calls of Twitter API or crawling.

In order to limit the research scope and control irrelevant variables, we conducted the following filtering process to the original data. First, we only keep users in the U.S., as the progress of the pandemic and vaccine development may vary greatly in different countries. Since we aim to analyze the change of sentiments of individuals, we only keep users with ≥ 3 tweets with a timespan of at least 100 days (which means the earliest post and the latest post of the user must be at least 100 days apart).

3.2 User Categorization

Both prior research [10] and common sense suggest that people's attitude toward the pandemic is related to personal backgrounds like

[1] https://www.kaggle.com/datasets/thusharanair/sma-pipeline

careers and age. Therefore, a major focus of this work is analyzing the reaction of different groups to the pandemic.

Table 1: Example of different types of users.

Category	User Profile
Healthcare Personnel	Respiratory Specialist Physiotherapist with an interest in airway collapse, COPD, and Bronchiectasis.
Media Workers	London's business newspaper - News, Opinion, and Analysis. For all distribution queries, see @CityAMDist.
Organizations	We empower students to challenge hate speech and develop strategies to tackle different types of extremism.
Scientists	Professor, School of Chemistry UNSW
General Population	Be yourself, everyone else is already taken. Oscar Wilde # Twinja

By combining prior research and manual analysis of posts in our dataset, we categorize users into **5** groups. **Healthcare personnel** are those working in medical-related fields, including doctors, nurses, and other medical professionals. Their working areas are closely related to the pandemic, so they're considered to receive more pressure than the general population and express opinions on COVID-related issues more often, especially those who combat the pandemic directly at the frontline. **Media workers** include journalists, reporters, and news publishers. Ideally, their posts often reflect professional responsibilities, aiming to report and verify the most updated COVID-related news. **Organizations** are official accounts of companies, unions, institutions, and so on. They often focus on maintaining public relations and business continuity during the pandemic, posting content related to the function of the organization. **Scientists** are researchers who frequently post evidence-based opinions or data-driven insights about the pandemic. Their responses often emphasize scientific rigor and caution, with a focus on advocating for evidence-based policies. Though we don't specify the field of study, we find the majority of scientists in our dataset work on biology, medicine, or sociology. **General population** is the group of individuals without specific professional ties to the pandemic that do not belong to the above categories. This group covers a wide range of users, and their reactions may vary widely based on their personal experiences and attitudes.

User profiles on Twitter typically serve as a short bio indicating the user's basic information and occupation. We provide the user profiles to GPT-4 [2], one of the most capable large language models currently, to categorize each user into one of the five categories above. One example of each group is shown in Table 1.

3.3 Sentiment Analysis

In this work, we adopted the valence-arousal model proposed by Russell [18] to analyze sentiments in tweets. The valence-arousal model is a widely adopted framework for describing emotional experiences along two primary dimensions: valence and arousal. Valence refers to the positivity or negativity of an emotion, while arousal denotes the intensity or activation level of the emotional experience. By plotting emotions on these two axes, the model provides a comprehensive way to classify a wide range of sentiments. This model gained broad application in psychology, neuroscience, and affective computing [22] due to its simplicity and effectiveness in capturing the complexity of human emotions using just two core dimensions. An illustration of the valence-arousal model is shown in Figure 2.

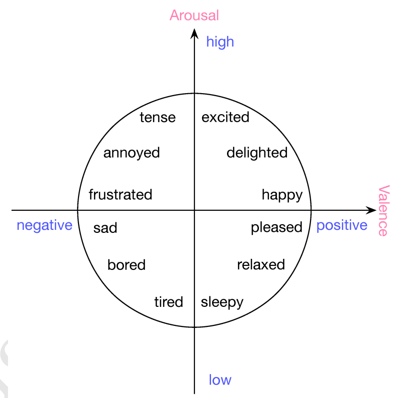

Figure 2: An illustration of the valence-arousal model of emotions. Image from Zhang et al. [24]

Neural networks have been widely adopted in various natural language processing tasks including sentiment analysis. A classical approach for sentiment classification is to first select an encoder model, namely, BERT[5], and then append a multi-layer perception (MLP) to the output of the encoder model which serves as the classifier to map the encoded representations to the desired output. The entire architecture is then trained end-to-end to optimize for the task-specific objective. However, there are two important reasons why we did not choose this approach. The first reason is most sentiment datasets in natural language processing only label the valence of the sentence (i.e. positive, negative, neutral). The second reason is the scale of Transformer-based models has grown explosively in recent years. Prior work suggests the relationship between model size and performance improvement can be approximately described by a power law function[9]. This indicates that training or fine-tuning sentiment classifiers to achieve state-of-the-art performance requires extensive training data and computational resources unavailable to us.

Therefore, we will explore two sentiment analysis methods that don't require mass computing in our work. The first method is freezing model parameters during finetuning and only updating the MLP part during training. We plan to use text-embedding-3-large[2] as the encoder and adopt EmoBank [3] to finetune our classifier. EmoBank consists of 10k sentences annotated with valence and arousal at 1-5 scales. The second method is directly utilizing the sentiment analysis API from Google[3] which provides both valence (ranging from -1 to 1) and arousal (ranging from 0 to infinity). We will annotate a small amount of data and evaluate the effectiveness

[2]https://platform.openai.com/docs/guides/embeddings
[3]https://cloud.google.com/natural-language/docs/reference/rest/v2/documents/analyzeSentiment

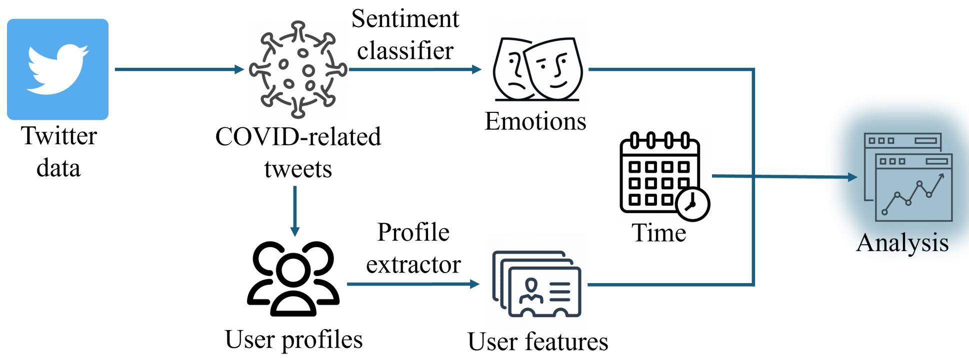

Figure 3: Procedure of the project.

of these methods. Since sentiment analysis methods are not our main focus, we will not elaborate on technical details.

The overall procedure of our work is shown in Figure 3.

4 Expected Outcomes

This study is expected to provide a comprehensive and detailed analysis of sentiment towards COVID-19 and related vaccine. We will focus on how public sentiment has evolved 1) across time, and 2) among different cohorts. Such analysis will be conducted at a fine-grained level, which means analyzing individuals separately. Advanced NLP techniques will be applied on the large-scale Twitter dataset, which is the theoretical basis for this work.

4.1 Outcomes

- **Individual sentiment trends** This is the foundation for all subsequent processing. We will collect tweets for each individual, analyze the sentiments and finally generate figures or introduce indicators to show their sentiment trends.
- **Aggregation for cohorts** We will aggregate the individual-level trends into five categories, namely healthcare personnel, media workers, organizations, scientists, and the general population. The classification will be based on user information, such as profile. Given that the aggregation will reduce cardinality, there may be a more understandable figure or chart for this part.
- **Analysis for general trends** Our research will track emotional changes over time at both the individual and collective levels, either within fixed length timeframes (weekly, monthly, etc.), or across predefined stages, which are correlated with major events of the pandemic. We will analyze to figure out which key events triggered such changes and how they happened. Such mapping may not guarantee complete accuracy but will, at least to some extent, provide guidance for future works. If the data is collected in fixed-timeframe format, we will also need to map each trend to specified period.
- **Analysis for cohorts** Currently, this is the stretch goal. We will use the data and trends to verify the conclusions of previous work, like [10], where the data was collected through social experiments rather than statistical analysis.

4.2 Contributions

- **Longitudinal Sentiment Analysis**: In this study, we focus on the temporal changes in sentiment toward the COVID-19 vaccine by analyzing Twitter comments over distinct pandemic stages. Previous work normally aggregated data for each stage first and then sketched the overall trends. In this study, the analysis will be individual-level, which brings more challenges for methodologies and higher requirements for datasets.
- **Targeted Interventions**: By identifying distinct sentiment patterns among various cohorts, more tailored interventions are possible for future pandemics. Different from previous work like [10], our work is based on large-scale dataset and more advanced sentiment analysis techniques. Our conclusion can either reinforce previous findings or correct some inaccuracies.

5 Schedule

5.1 Contribution Statement

In this section, we show each group member's roles and responsibilities. Note that these roles may be subject to change based on our actual progress.

- **Bohan Wu**: "Related Work" and "Expected Outcomes" sections in the proposal. Dataset and data pre-processing.
- **Tianyang Liao**: "Introduction" section in the proposal. Experimental evaluation.
- **Peixuan Han**: "Methodology" section in the proposal. Exploring sentiment analysis tools. Analyzing user profiles.

5.2 Timeline

In Table 2, we show the overall timetable for our project.

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Table 2: Project Timeline

Phase	Estimated Time
Data collection & preprocessing	Oct 2024
Proposal writing	Oct 2024
Model training & sentiment analysis	Oct 2024 - Nov 2024
Emotion trend analysis	Nov 2024
User profile × emotion analysis	Nov 2024 - Dec 2024
Final report writing	Nov 2024 - Dec 2024

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