Aspect-Level Sentiment Analysis of Filipino Tweets During the COVID-19 Pandemic

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Abstract: During the COVID-19 pandemic, X (formerly known as Twitter) was teeming with rich discussions as people shared their experiences and concerns. Understanding the sentiments in these tweets could aid in gauging public reactions and enhancing public health communication. While some studies analyze public health sentiments, few specifically focus on aspect-level sentiments in the Global South. In this study, we examine tweets published in the Philippines during the COVID-19 pandemic and aspects relevant to the pandemic. The sentiment polarities of tweet-aspect pairs are annotated. We analyze these pairs to understand the sentiments expressed during this period. These insights can improve health communication in the Philippines by assessing public receptiveness to policies, monitoring events that influence sentiment, and identifying communication gaps. Notably, we observed disproportionately high amounts of negative sentiment toward the Sinopharm and Sinovac vaccines. This sentiment indicates distrust and racial bias against Chinese brands. Moreover, the consistent negative sentiment toward face shields over an extended period highlights shortcomings in health communication about their effectiveness.

1 INTRODUCTION

The Internet has become an essential tool for day-to-day communication. Social media platforms like X facilitate the widespread sharing of people's thoughts, opinions, and knowledge. During the COVID-19 pandemic, X was teeming with rich discussions as people shared their experiences and concerns (Pastor, 2020; Wang and Chen, 2022). The vast amounts of data generated through online discourse can be processed to yield valuable insights (Ghani et al., 2019).

A common method for extracting information from text data is sentiment analysis. Sentiment analysis, or opinion mining, refers to the process of extracting opinions or sentiments from bodies of texts (Pang et al., 2008). It has a wide variety of applications, such as monitoring social media, processing customer reviews, and deciding political campaign strategies (DeNardis and Hackl, 2015; Ramteke et al., 2016; Salinca, 2015).

One particularly promising application of sentiment analysis lies in health communication. Health communication is the study of communication strategies designed to influence individuals to adopt behaviors beneficial to their health (Schiavo, 2013). Sentiment analysis can be used to assess the public's risk perception and attitudes toward infection control strategies (Alhajji et al., 2020). In addition, it can measure the public's concern about diseases (Cabling et al., 2018; Himelboim et al., 2020; Ji et al., 2015). However, much of the existing research is situated in the Global North (Wang and Chen, 2022), which can have vastly different experiences compared to countries in the Global South (Balfour et al., 2022). This study uses sentiment analysis to examine public reactions and identify communication gaps in the Philippines during the COVID-19 pandemic.

Sentiment analysis is mainly done at three levels of granularity (Liu, 2012). The first level is document-level, which extracts a sentiment from an entire document (Cabling et al., 2018). This is use-

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ful in cases where the documents were selected to express opinions on a fixed entity, but it is not applicable when documents have multiple entities. The second level is sentence-level, which aims to assign sentiments to each sentence in a document (Himelboim et al., 2020; Wang and Chen, 2022). This assumes that each sentence expresses an opinion on one entity but will fail when a sentence contains multiple entities. The third level is aspect-level or aspect-based sentiment analysis (ABSA), which extracts a sentiment towards a given aspect or entity in a sentence. Knowledge about the specific target of the opinion allows for a more fine-grained analysis of sentiments. For instance, smartphone reviews may contain sentiments about various aspects of the phone, such as battery life, camera, and screen quality. Smartphone manufacturers may use the insights from aspect-level sentiment analysis to make targeted improvements.

Jang et al. (2021) conducted an ABSA study analyzing Twitter data during the COVID-19 pandemic in North America. Their research uncovered various negative topics linked to the pandemic, including anti-Asian racism and the spread of misinformation. They employed topic modeling to identify topics and aspects. They then used a combination of English lexicons, part-of-speech tagging, and dependency parsing for sentiment polarity classification.

A significant challenge in sentiment analysis for the Global South is the lack of tools for processing multilingual text. One approach, employed by Mathayomchan et al. (2023), involves filtering out non-English tweets and then applying existing tools to the remaining English tweets. Unfortunately, this method excludes tweets written in local languages or those code-mixed with English.

In this study, we examine tweets published in the Philippines during the COVID-19 pandemic and aspects relevant to the pandemic. This is done to gain a deeper understanding of public sentiment and the factors that influence it during this critical period. We manually identified the topics and aspects and then classified sentiment polarity. We then study the sentiments by aggregating aspect-level sentiments in various ways. These insights can improve health communication in the Philippines by assessing public receptiveness to policies, monitoring events that influence sentiment, and identifying communication gaps.

2 METHODOLOGY

The data used in this study originate from the tweets collected by Chan et al. (2022). These tweets were posted between December 4, 2020, and June 4, 2021. The tweets were filtered to ensure they originate from the Philippines based on geolocation and contain at least one of the specified health-related keywords: "*covid-19*," "*covid*," "*coronavirus*," "*corona*," "*tb*," "*tuberculosis*," "*WorldTBDay*," or "*TBFreePh*" (Chan et al., 2022). Aspect terms were selected based on topics frequently discussed during the pandemic, including but not limited to different vaccine brands, travel bans, community quarantine, the use of masks/face shields, hospital capacity, government agencies, and isolation facilities. Aspects related to tuberculosis, such as "*cough*," "*ubo*," and "*fatigue*," were excluded to avoid conflating tuberculosis sentiments with those of COVID-19. In total, 590 aspects were identified (Guzman, 2024).

Two human annotators were hired to label the sentiment polarity towards an aspect term in a given tweet. These annotators are native Filipino speakers fluent in English and have backgrounds in jobs requiring communication skills in both languages, such as teaching. Before starting the annotation process, the annotators underwent a brief training session. They were instructed to classify each tweet-aspect pair into one of four categories: *positive* when the sentiment towards the aspect is positive, *negative* when the sentiment towards the aspect is negative, *neutral* when the sentiment towards the aspect is neither positive nor negative, and *no_relation/conflicting* when there is no sentiment expressed towards the aspect or when the sentiment is conflicting. The annotators were also provided with examples to illustrate each category.

To reduce the noise in the labeling, tweet-aspect pairs labeled as *no_relation/conflicting* were discarded. The pairs where the annotations do not match were also removed, such as when one annotator labels a pair as *positive* while another labels it as *negative*. A total of 6,600 pairs remained after the removals. Among these, 2,840 are labeled as *negative*, 2,705 as *neutral*, and 1,055 as *positive* (Guzman, 2024).

We evaluated the inter-annotator agreement between the two hired annotators using Cohen's Kappa statistic κ before discarding annotations (Cohen, 1960). The calculated κ value was 0.5116, suggesting a degree of agreement but at a relatively low level (McHugh, 2012).

3 RESULTS

Aspects are categorized into different topics, which can be further divided into subtopics. This approach enables us to aggregate sentiments at various levels of generality. The aspects are categorized into five main topics: *Facilities*, *Government*, *Responses*,

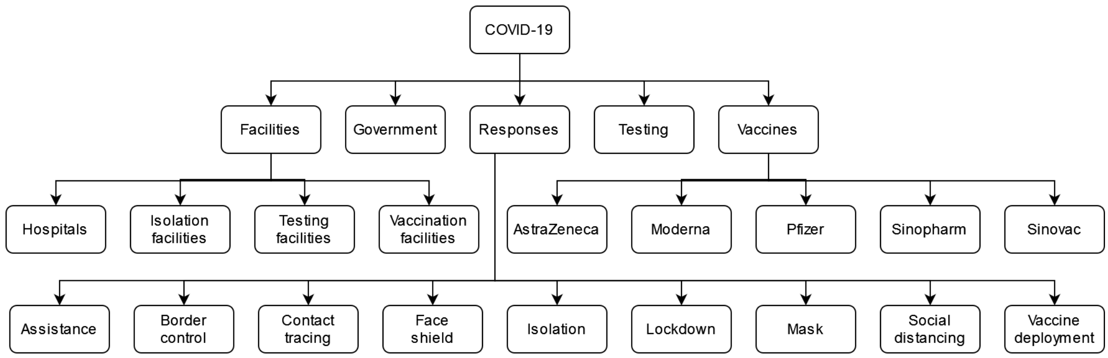

Figure 1: Categorization of aspects into selected topics and subtopics. Aspects related to facilities, government organizations or officials, pandemic responses or policies, testing, and vaccines are assigned to specific topics under COVID-19. Within the *Vaccines* topic, particular vaccine brands are classified into subtopics. Similarly, frequently discussed pandemic responses within the *Responses* topic are organized into subtopics. Finally, important pandemic facilities within the *Facilities* topic are further categorized into subtopics.

Testing, and *Vaccines*. Aspects related to facilities, government organizations or officials, pandemic responses or policies, testing, and vaccines are assigned to these topics. Within the *Vaccines* topic, specific vaccine brands are classified into the subtopics: *AstraZeneca*, *Moderna*, *Pfizer*, *Sinopharm*, and *Sinovac*. Frequently discussed pandemic responses within the *Responses* topic are categorized into the subtopics: *Assistance*, *Border control*, *Contact tracing*, *Face shield*, Isolation, *Lockdown*, *Mask*, *Social distancing*, and *Vaccine deployment*. Finally, important pandemic facilities within the *Facilities* topic are classified into the subtopics: *Hospitals*, *Isolation facilities*, *Testing facilities*, and *Vaccination facilities*. Any aspect within the five main topics that do not fit the aforementioned subtopics is not further categorized (Guzman, 2024). A diagram of the selected topics and subtopics is shown in Figure 1.

Figure 2 shows the distribution of sentiments across various topics. Each topic contains a significant portion of neutral sentiments. Notably, a considerable amount of negative sentiment is expressed towards *Government*, *Responses*, and *Facilities*. In contrast, *Vaccines* elicits more positive sentiments.

Figure 3 displays the sentiment distribution of subtopics of *Vaccines*. Each subtopic shows a significant proportion of neutral sentiments. Notably, *AstraZeneca* and *Pfizer* exhibit a moderate amount of positive sentiments. Meanwhile, *Sinopharm* and *Sinovac* have larger amounts of negative sentiments.

Figure 4 depicts the distribution of sentiments within the *Responses* subtopics. Most of them show low amounts of positive sentiments. The exception is *Mask*, which is predominantly positive. Conversely, *Face shield* and *Lockdown* mainly exhibit negative sentiments. Similarly, Figure 5 shows that nearly all *Facilities* subtopics have a low proportion of positive sentiments. The only exception is *Vaccination facilities*, which predominantly shows positive sentiments.

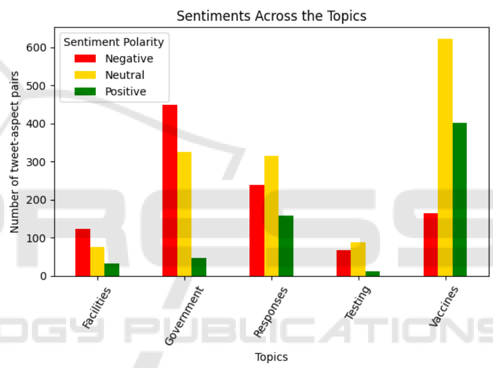

Figure 2: Distribution of sentiments across various topics. Each topic exhibits a substantial proportion of neutral sentiments. There are significant amounts of negative sentiment toward *Government*, *Responses*, and *Facilities*. Meanwhile, *Vaccines* elicits more positive sentiments.

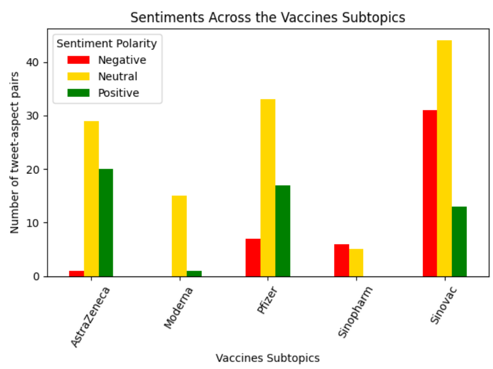

Figure 3: Distribution of sentiments among subtopics of *Vaccines*. Each subtopic has a large portion of neutral sentiments. *AstraZeneca* and *Pfizer* exhibit moderate amounts of positive sentiments. On the other hand, *Sinopharm* and *Sinovac* have large proportions of negative sentiments.

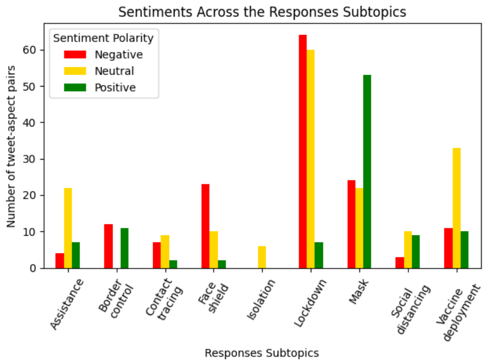

Figure 4: Distribution of sentiments among subtopics of *Responses*. Most subtopics show low amounts of positive sentiments, except for *Mask*, which is primarily positive. In contrast, *Face shield* and *Lockdown* predominantly exhibit negative sentiments.

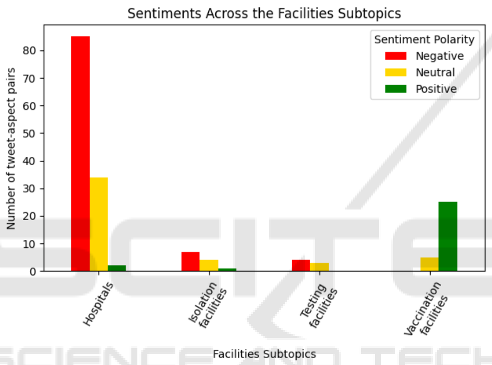

Figure 5: Distribution of sentiments among subtopics of *Facilities*. Almost all subtopics show low levels of positive sentiment. The exception is *Vaccination facilities*, which is predominantly positive.

Next, we visualize trends in selected topics and subtopics by separating tweets by month. In Figure 6, we see that the sentiment for *Sinovac* is consistently negative and neutral. However, there has been an increasing trend in positive sentiment since March. A similar upward trend in positive sentiments is observed for *AstraZeneca*.

In Figure 7, we observe an increase in positive sentiment regarding *Vaccine deployment* in March and April. However, there is a spike in negative sentiment in May. Discussions about *Assistance* rose in April, though it is rarely discussed in the other months. Furthermore, *Face shield* consistently evokes negative sentiment. Notably, *Lockdown* received a substantial increase in negative sentiment in March. During March and April, we also observed a surge in negative sentiments directed towards the *Government* and *Testing*, as illustrated in Figure 8.

4 DISCUSSION

The hierarchical nature of this approach facilitates a better understanding of sentiments. We notice predominantly positive and neutral sentiments when examining the distribution of sentiments related to *Vaccines*, as shown in Figure 2. However, delving into the subtopics in Figure 3 reveals a disproportionately high amount of negative sentiment targeting *Sinopharm* and *Sinovac*. This discrepancy suggests a lack of trust in the Sinopharm and Sinovac vaccines.

The overall sentiment towards the *Responses* and *Facilities* topics is mostly negative and neutral. Nonetheless, the *Mask* and *Vaccination facilities* subtopics stand out with a large amount of positive sentiment, as depicted in Figures 4 and 5. This reflects public support for wearing masks during the pandemic and satisfaction with vaccination sites.

Beyond analyzing sentiment distribution, we delve into the contents of the tweets to identify common reasons for negative sentiments. Our goal is to understand these causes in order to find potential solutions. Firstly, we consider some tweets from the *Facilities* topic expressing negative sentiments:

- "*there are no more hospital beds in ncr. the sooner the government acknowledges this, the quicker we can get any intervention.*"
- "*only 27k people tested for two days in a row. almost the same number two weeks ago, before the start of ecq kala ko ba increase testing capacity?*"

A common concern is the potential of hospital or ICU beds reaching full capacity. This worry is highlighted in a news article by Tomacruz (2021a), which reports an alarming occupancy of ICU beds in Metro Manila. Another common concern observed in the tweets is insufficient testing capacity, which was also acknowledged by government officials (Luna, 2020). The emphasis on facilities highlights the efforts of Filipinos on social media to frame the COVID-19 problem as structural and societal rather than solely individual. This emphasis exposes the existing flaws in the Philippine healthcare system and problematic legal approaches to a public health crisis (Bernadas and Ilagan, 2020; Navera and Bernadas, 2022).

We turn our attention to the tweets from the *Face shield* and *Lockdown* subtopics under *Responses*, as they predominantly exhibit negative sentiments:

- "*2020 mecq....gcq...ecq 2021 granular lockdown, hard/soft lockdown.... tapos heightened gcq... ano pa naiisip nyong forms ng quarantine?*"
- "*i still don't get the rationale for the use of face shields when in fact, it did not even lower the*

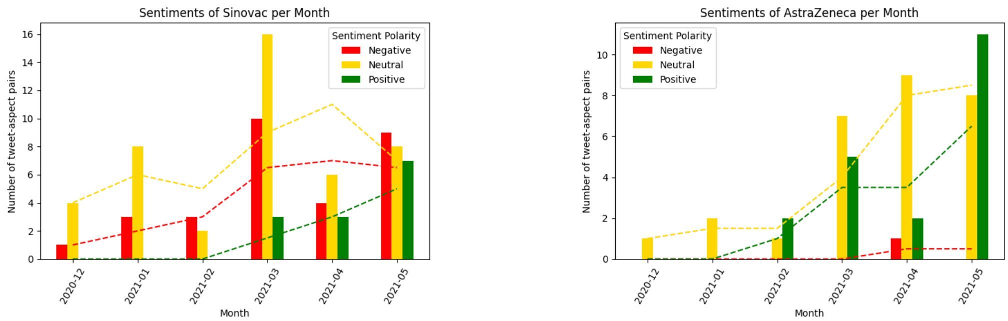

Figure 6: Trends in sentiments on *Vaccines* subtopics. The trendlines were calculated using 2-month moving averages. The sentiment for *Sinovac* is consistently negative and neutral. Nonetheless, there has been a notable increase in positive sentiment since March. A similar rise in positive sentiments is observed for *AstraZeneca*.

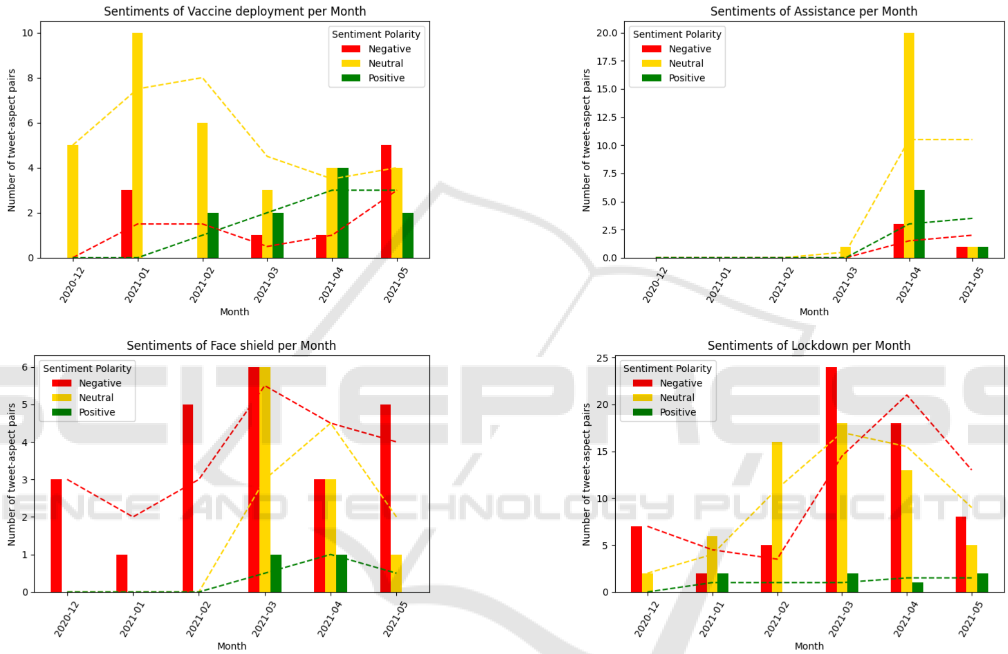

Figure 7: Trends in sentiments on *Responses* subtopics. The trendlines were calculated using 2-month moving averages. We observe an increase in positive sentiment regarding *Vaccine deployment* in March and April. However, there was a notable rise in negative sentiment in May. Furthermore, *Face shield* consistently evokes negative sentiment. Discussions about *Assistance* rose in April, though it is rarely discussed in the other months. Finally, there was a substantial rise in negative sentiment concerning *Lockdown* in March.

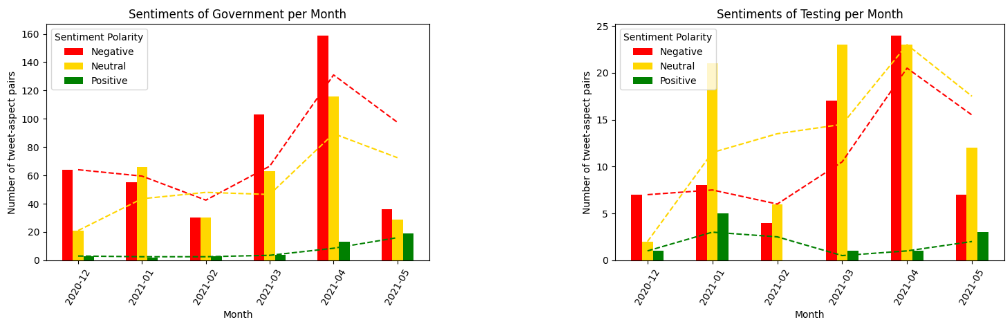

Figure 8: Trends in sentiments on the *Government* and *Testing* topics. The trendlines were calculated using 2-month moving averages. The positive sentiments are consistently low towards *Government* and *Testing*. In March and April, there was a surge in negative sentiments directed at these topics.

covid cases? it just adds plastic trash. so, can someone shed some light? fuck rules!"

- "*after a year of covid-19 pandemic in the country, we have the following: world's longest lockdown last to legally vaccinate in southeast asia best*"

The negative sentiments toward face shields stem from skepticism about their effectiveness, leading to online debates and controversy (Pamintuan, 2021). Health agencies can combat this by designing messages focused on the positive outcomes of preventive measures, known as gain-framing. Meanwhile, negative sentiment towards lockdowns stems from the prolonged duration, notably being one of the world's longest lockdowns (Patag, 2021; See, 2021). Additionally, people expressed dissatisfaction with the complicated and seemingly erratic types of community quarantine (Gotinga, 2020).

We examine the tweets related to the *Sinovac* and *Sinopharm* subtopics under *Vaccines*, which had a disproportionately high amount of negative sentiment. During this analysis, we identified some interesting words frequently brought up in these tweets. Figure 9 shows the most frequent words. Certain words, like vaccine names, are expected to have high frequencies. However, some unexpected terms, namely "*chinese*" and "*efficacy*," surfaced with notable frequency. This discovery prompts a more focused examination of these specific terms.

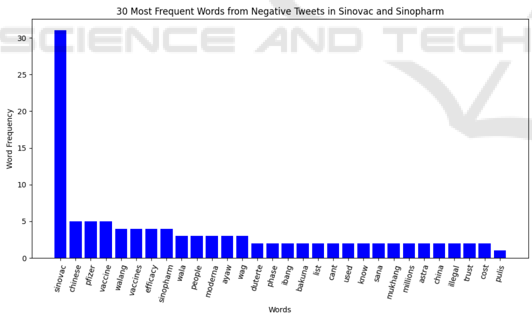

Figure 9: Frequently occurring words from negative tweets in the *Sinovac* and *Sinopharm* subtopics. Certain words, like vaccine names, are expected to have high frequencies. However, some unexpected terms, namely "*chinese*" and "*efficacy*," surfaced with notable frequency.

We investigate how the words "*chinese*" and "*efficacy*" relate to negative sentiments by filtering tweets that contain either of these keywords:

- "*may history kasi ang sinovac ng bribery sa mga chinese official dati.*"
- "*sinovac ang vaccine dito sa qc uhuhuhuhuh i dont trust chinese product fuuuuuuk*"
- "*in chinatown/chinese warehouses/chinese owned condos located from batanes to jolo millions upon millions of sinovac/sinopharm vaccines are "label switching" into pfizer/biontech, astrazeneca, moderna, j&j, covavax!!! very, very alarming!!!*"
- "*people are hesitant not on the vaccines in general but on the efficacy and safety profile of your favorite chinese brand. people want pfizer, az, and moderna. throw sinovac in the trash.*"

Negative sentiment may be linked to Sinovac Biotech's past involvement in bribery cases with Chinese drug regulators (Bergonia, 2020). Additionally, rumors about fake vaccines contribute to the negative perception of these vaccines (The Food and Drug Administration of the Philippines, 2021; The Philippine Star, 2021). A significant point of contention about the Sinovac vaccine is its low efficacy. Critics, including lawmakers and former advisers, question the government's decision to procure the Sinovac vaccine. They argue that other vaccines have higher efficacy rates at lower costs and express concerns about the lack of transparency in Sinovac's clinical trials (Bondoc, 2021; Jalea, 2020; Romero, 2020). Moreover, the frequent occurrence of the term "*chinese*" in a negative context reinforces the racialization of health issues and reflects the precarity of Sino-Philippines relations (Cabañes and Santiago, 2023).

Lastly, we analyze the trends in certain topics and subtopics. The rise of positive sentiment towards *Sinovac*, depicted in Figure 6, coincides with the start of the COVID-19 vaccine rollout in the Philippines on March 1, 2021. This event likely contributed to the public's favorable perception of the vaccine brand. Similarly, the vaccine rollout likely influenced the increase in positive sentiment toward *Vaccine deployment*, as illustrated in Figure 7.

It was announced near the end of March that low-income Filipinos were set to receive supplemental aid (Rey, 2021). This development reflects a rise in discussions about *Assistance* in April, as seen in Figure 7. Furthermore, we observed that *Face shield* consistently evoked negative sentiment. This persistent negativity suggests that health communication about their benefits has been inadequate for an extended period. Public health campaigns should promote the benefits of using face shields more assertively to bridge this communication gap. Lastly, the substantial increase in negative sentiment toward *Lockdown* in March 2021 coincides with the one-year anniversary of the initial lockdown implemented in March 2020 (Medialdea, 2020). By this time, many expressed dissatisfaction with the lockdown, which had become one of the world's longest (Patag, 2021; See, 2021).

In March and April, there was a surge in negative sentiments towards the *Government* and *Testing*, as illustrated in Figure 8. Much of this negativity stemmed from the inadequacy of the pandemic response despite the prolonged lockdown. Criticisms directed at the government included a lack of acknowledgment or downplaying of problems and mistrust in reported numbers. As for testing, the main issue was the absence of mass testing (Cabico, 2021).

Despite the insights gained from this study, we have encountered several limitations. The reliance on manually annotated data posed several challenges. First, the manual labeling process is labor-intensive and difficult to scale. Second, sentiment analysis has inherent subjectivity, as individual biases can influence annotations. Consequently, the resulting dataset was relatively small, consisting of only 6,600 tweet-aspect pairs. This limited sample may not fully represent the broader population's sentiments.

5 CONCLUSIONS

In this paper, we studied the tweets collected by Chan et al. (2022) and the tweet-aspect sentiment polarity annotations of Guzman (2024). We analyzed this data using three approaches.

First, we examined the distribution of sentiments at different levels of granularity. We have found a disproportionately high amount of negative sentiment specifically targeting *Sinopharm* and *Sinovac*. This sentiment suggests a lack of trust in the Sinopharm and Sinovac vaccines. Equally important, this study reinforces health as racialized and reflects the complexity and precarity of the Sino-Philippines relationship (Cabañes and Santiago, 2023), even before the pandemic. On the other hand, the sentiment towards the *Mask* and *Vaccination facilities* subtopics stand out with predominantly positive sentiments. This reflects public support for wearing masks during the pandemic and satisfaction with vaccination sites.

Second, we explored the content of tweets to pinpoint common reasons for negative sentiments. For the *Facilities* topic, we have found that a common theme is the possibility of hospitals reaching full capacity and insufficient testing capacity. In the *Face shield* and *Lockdown* subtopics, negative sentiments revolve around skepticism regarding the effectiveness of face shields, prolonged lockdown duration, and complicated types of community quarantine. Concerning the *Sinovac* and *Sinopharm* subtopics, common issues include Sinovac Biotech's past involvement in bribery cases with Chinese drug regulators, rumors about fake vaccines, the low efficacy of Sinovac with its relatively high price, and lack of transparency in clinical trials.

Finally, we examined trends in the sentiments to identify events that might have influenced changes in sentiment. In March, people showed more positive sentiment toward *Sinovac* and *AstraZeneca* likely the rollout of COVID-19 vaccines in the Philippines. During the same period, negative sentiment towards *Lockdown* increased as it marks the one-year anniversary of the initial lockdown. This anniversary likely contributed to the rise in negative sentiment toward *Government* and *Testing*. The negative sentiment was driven by criticisms of the inadequacy of the pandemic response and the lack of mass testing despite the prolonged lockdown. Furthermore, sentiment towards *Face shield* remained consistently negative, indicating poor public health communication about their effectiveness over an extended period. To address skepticism and misinformation regarding face shields, health officials should adopt a more proactive and assertive approach to emphasizing their benefits.

Future studies should explore ways to overcome these limitations. For manual annotations, we recommend providing more detailed guidelines and examples to increase inter-annotator agreement. Additionally, future research could investigate integrating machine learning techniques to complement manual annotation, thereby facilitating data collection on a larger scale. Moreover, collecting data from different periods and regions could yield further insights.

We recommend exploring alternative topics related to the pandemic. Our categorization of topics was selected based on what we deemed relevant during the pandemic. However, other applications may yield topics and hierarchies different from those in Figure 1. For instance, one may want to track topics and subtopics related to the spread of misinformation or mental health. A different categorization could help gain insights into new topics and subtopics.

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