Safety-focused vaccine tweets exhibit systematically *** sentiment than access-focused tweets

Group #12 - Model Citizens
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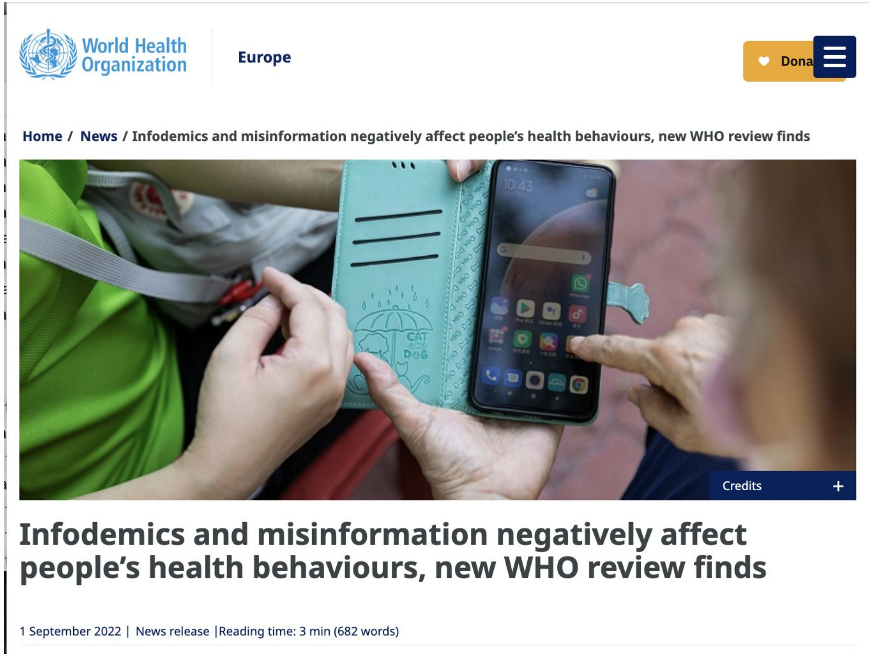
Background - Why Does This Matter?

- The World Health Organization describes “infodemics” as a serious problem–misinformation influences health behaviors, including decisions about prevention and vaccination ([WHO](WHO)).
- Vaccine discourse falls under themes–such as safety concerns, misinformation claims, access issues, and general update
- Social media is a primary channel for vaccine discourse.



Research Question:

Are tweets focused on vaccine safety concerns more negative than tweets focused on access or eligibility?

Hypothesis and Modelling Approach

In order to further explore theme-specific sentiment differences our group developed the following hypothesis:

Tweets centered on safety or side effects will exhibit lower (more negative) sentiment scores than access-focused tweets.

Our Modelling Approach:

1. Theme classification using keyword dictionaries
2. Sentiment scoring using VADER (optimized for short informal text)
3. Statistical comparison of sentiment across themes
4. Regression analysis controlling for tweet characteristics

Data Acquisition and Explanation - Kaggle Dataset

Covid-19 Vaccine Tweets with Sentiment Annotation

Tweets about COVID-19 Vaccines with manually annotated sentiments

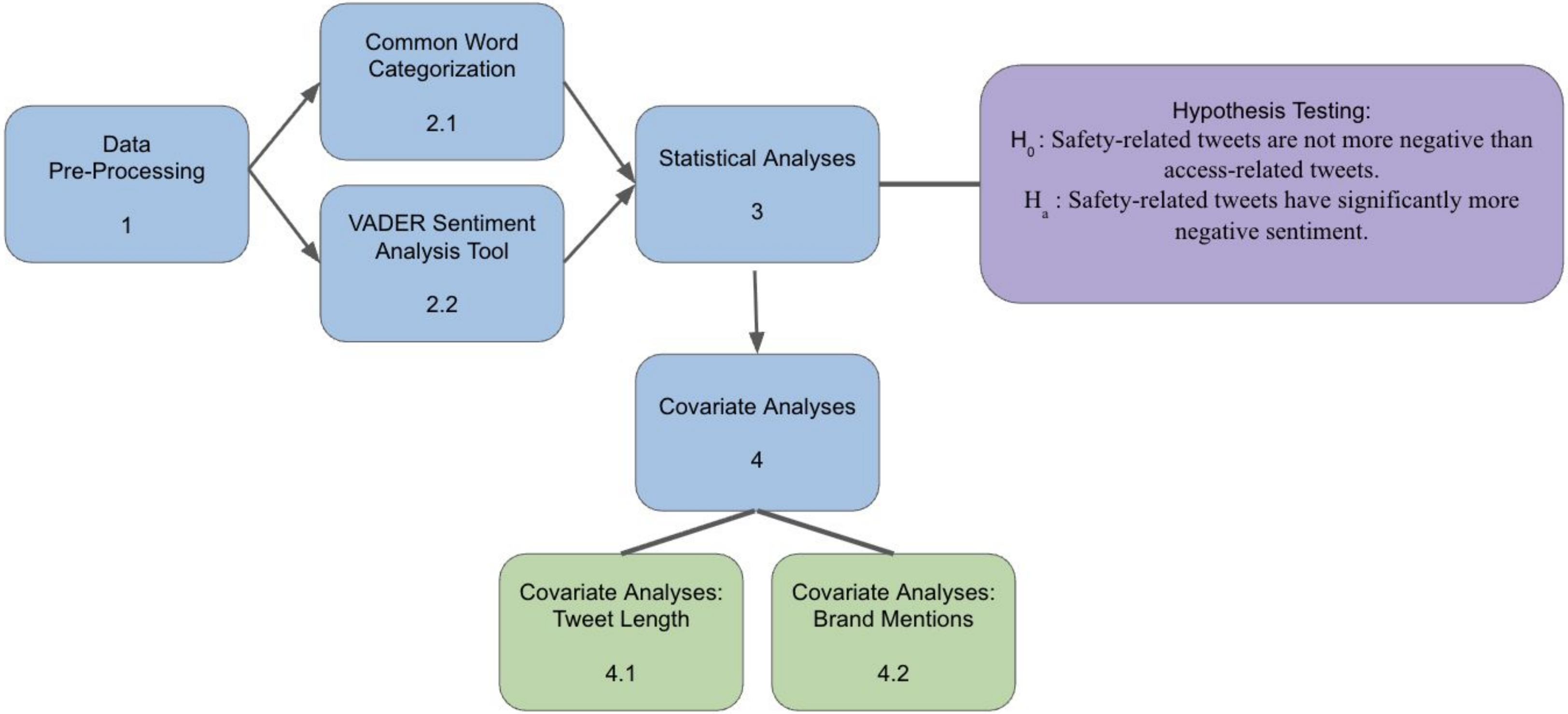
Contains 6000 observations of tweets scraped from Twitter, containing the following COVID vaccine keywords: Pfizer/BioNTech, Sinopharm, Sinovac (both Chinese-produced vaccines), Moderna, Oxford/Astra-Zeneca, Covaxin, and Sputnik V vaccines.

Each tweet is labelled with a 'tweet_id' and a sentiment label (Negative = 1, neutral = 2, positive = 3).

<u>For our analysis, we are only interested in the tweet text itself</u>

Column	Description	Potential Responses
Tweet_ID	A unique numerical ID referencing a tweet.	1360342002961940483,1382896334886248448
Label	Describes the sentiment of the tweet, Positive = 3, Neutral = 2, Negative = 1.	3, 2
Tweet_Text	Contains the contents of the tweet.	Bharat's COVID shot shows high immune response, further study needed 4 elderly\n\nPeer-reviwed study published in medi journal Lancet on Monday is another positive 4 Bharat Biotech,has attracted interest from more tn 40 countries\n#VaccineMaitri \n#COVID19 \n#COVID19Vaccine \n#Covaxin,

Analysis Plan and Modelling Approach



Tricky Analysis Decision: Keyword Dictionary Construction

- Plan specified using the top 50 most frequent words to categorize tweets into themes, but no top-50 words mapped to "eligibility" → 0 matches
- Stuck with the plan: adding words outside the top 50 would be cherry-picking keywords to force a result, undermining the data-driven approach
- Eligibility not appearing in the top 50 is itself a finding, it wasn't a prominent topic in vaccine tweets during this period
- Core analysis (safety vs access) was unaffected ($p < 0.000001$)

Biases/Uncertainties

Dataset Biases

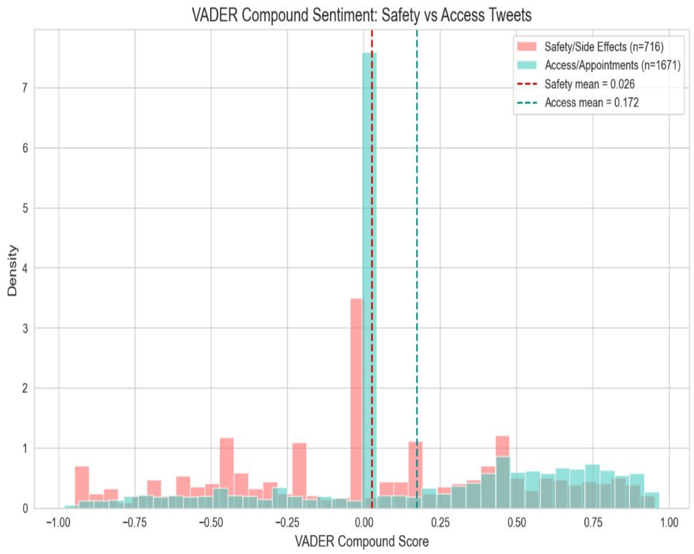
- Only includes Twitter users, who are not representative of the general population.
- Users tend to post more extreme or opinionated content.
- Theme classification relies on keyword dictionaries, which can miss indirect mentions of safety or access.
- VADER sentiment analysis may misinterpret sarcasm, slang, or context.

Mitigating Bias

- Cleaned text by removing URLs, @mentions, and hashtags.
- Used robust statistical tests (Welch's t-test) that allow unequal variance.
- Controlled for tweet length and brand mentions in regression analyses.

Quantifying Uncertainty

- Standard deviations of sentiment scores show variability within themes.
- Welch's t-test (α = 0.05) formally tests differences in means.
- Low p-value (< 0.001) confirms safety tweets are significantly more negative.
- Regression models with covariates validate that results are robust despite confounders.

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Significance level: alpha = 0.05

Safety tweets  (n = 716):
  Mean VADER compound: 0.0261
  Std:                 0.4880

Access tweets  (n = 1671):
  Mean VADER compound: 0.1724
  Std:                 0.4351

t-statistic:         -6.9268
p-value (one-sided): 0.000000
```

Results

Hypothesis: Tweets centered on safety or side effects will exhibit lower (more negative) sentiment scores than access-focused tweets.

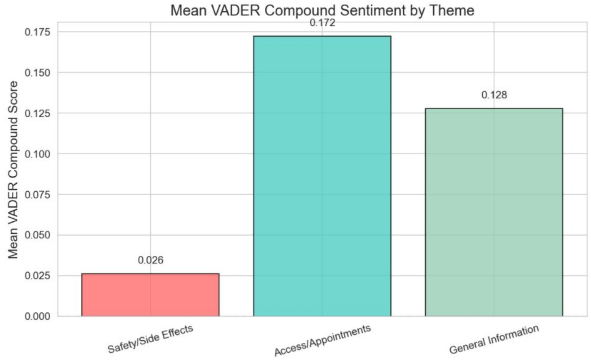
Key Findings:

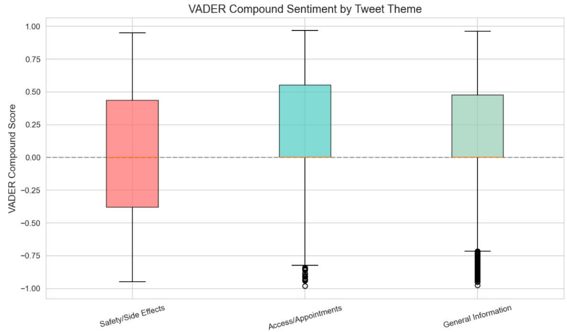
- **Safety tweets** have significantly lower sentiment (VADER mean = 0.0261) than **access tweets** (VADER mean = 0.1724).
- **t-test:** t = -6.93, $p < 0.001$ → reject H0.
- **Regression:** theme_safety coefficient = -0.13, $p < 0.001$ → effect remains controlling for tweet length and brand mentions.

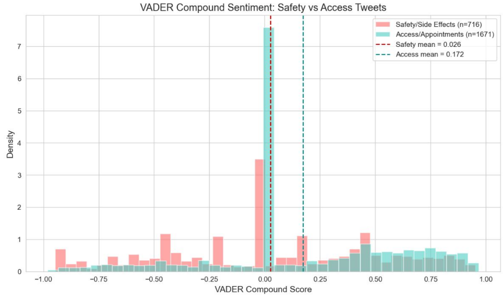
Additional Insights:

- Tweet length slightly increases positivity; brand mentions have no effect.
- Overall sentiment is highly variable ($R^2 \approx 0.009$), suggesting additional factors influence tweet sentiment.

Conclusion: Tweets discussing **safety or side effects are consistently more negative**, confirming the hypothesis.







Expanding Analysis & Future Questions

Exploration:

- Track sentiment over **time/events** (approvals, policy changes to vaccine mandation)
- Compare **other social media platforms (**reddit, threads, substack)

Improvements:

- Use advanced models for **sarcasm and context**
- Include **geographic/demographic data** to reduce bias

Further Questions:

- How do tones/perspectives vary across **regions/communities**?
- Are there **triggers** for spikes in **negative** sentiment (specific words, policies) ?

References

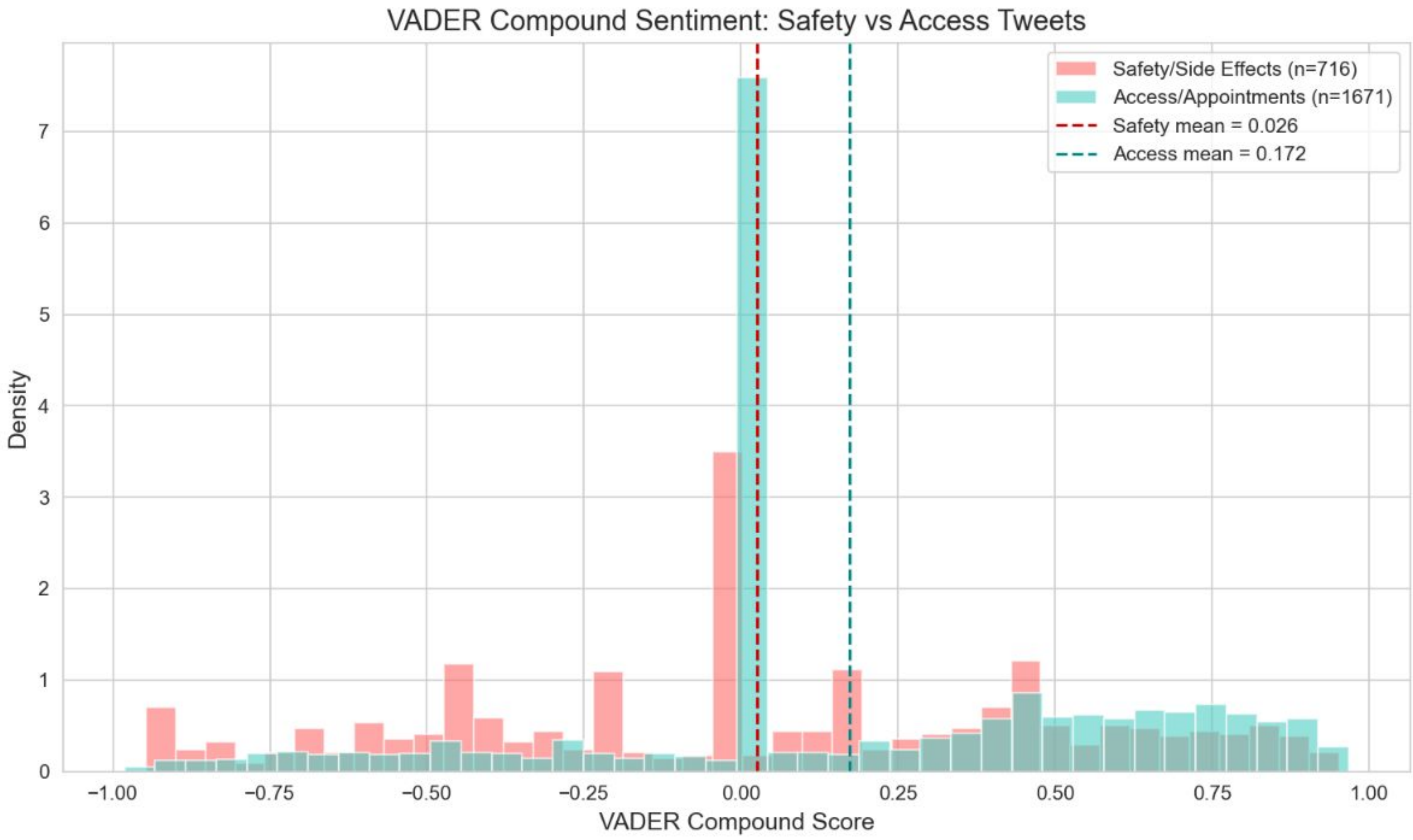
[1] shainabanduri, “Project-1-DS4002,” GitHub repository. Available: https://github.com/shainabanduri/Project-1-DS4002/tree/main

[2] "Covid-19 Vaccine Tweets with Sentiment Annotation," Kaggle dataset. Available: https://www.kaggle.com/datasets/datasciencetool/covid19-vaccine-tweets-with-sentiment-annotation

[3] World Health Organization Regional Office for Europe, "Infodemics and misinformation negatively affect people's health behaviours -- new WHO review finds," Sep. 1, 2022. Available: https://www.who.int/europe/news/item/01-09-2022-infodemics-and-misinformation-negatively-affect-people-s-health-behaviours--new-who-review-finds

[4] Centers for Disease Control and Prevention, "Strengthen Vaccination Communications (IQIP)," Jun. 18, 2024. Available: https://www.cdc.gov/iqip/hcp/strategies/strengthen-vaccination-communications.html

[5] C. J. Hutto and E. Gilbert, "VADER: A parsimonious rule-based model for sentiment analysis of social media text," Proceedings of the International AAAI Conference on Web and Social Media, vol. 8, no. 1, 2014. Available: https://doi.org/10.1609/icwsm.v8i1.14550


VADER Compound Sentiment: Safety vs Access Tweets
Safety/Side Effects (n=716)
Access/Appointments (n=1671)
Safety mean = 0.026
Access mean = 0.172
Density
0
1
2
3
4
5
6
7
−1.00
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
VADER Compound Score