# Vaccine Misinformation – A Twitter Pandemic

A study of the spread of COVID-19 vaccine misinformation on a social-media platform

# Background

- Many diseases have been vanquished thanks to vaccines.
- Vaccine hesitancy can threaten this progress.
- One cause of vaccine hesitancy is vaccine misinformation.
- Vaccine misinformation spreads fast through social media.
- To counter misinformation, you need a thorough understanding of it.
- In this study, we will look at misinformation about COVID-19 vaccines.

# Project Idea

- **Part 1. Topic Modeling**
  - Extract topics from a set of tweets containing vaccine misinformation.
  - RQ: What are the main misconceptions?
- **Part 2. Network Analysis**
  - Build a retweet network of the main misinformers.
  - RQ: How are they connected? Who is retweeting whom?
  - RQ: How many misinformers are responsible for what part of the spread?

# Related Work

- **Hayawi et al. 2021**
  - Set of 15k tweets, manually labeled for vaccine misinformation.
  - Set of 15M unlabeled vaccine-related tweets.
  - BERT-based vaccine-misinformation classifier. F1-score: 0.98
- **Cotfas et al. 2023**
  - Set of 5.7k tweets, manually labeled for vaccine hesitancy.
  - RoBERTa-based vaccine-hesitancy classifier, with three classes. Accuracy: 95.57%
  - Topic modeling on vaccination-hesitancy tweets.
- **My contributions**
  - Topic modeling on vaccination-misinformation tweets.
  - Examine how tweeters' are connected, by building retweeter network.

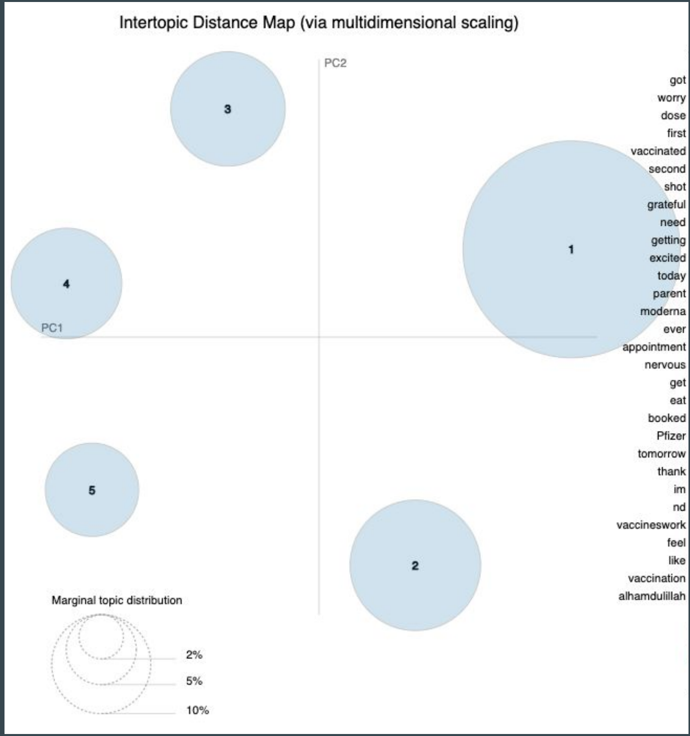
# Topic Modeling: Methodology

- Use Latent Dirichlet Allocation (LDA) to extract topics
  - from misinformation tweets
  - from *non*-misinformation tweets
- Tune hyper-parameters
  - Number of topics
  - min_df: minimum portion of tweets a term must occur in
  - max_df: maximum
- Evaluate
  - Coherence and diversity metrics:
    - C_v,
    - C_npmi
    - Jaccard Diversity
  - Topic labels: manual evaluation

# Misinformation Topics


1. ***Experimental and untested*** : experimental, untested, virus, rushed;
2. ***Experimental therapy*** : experimental, therapy, gene, mRNA;
3. ***Experimental gene therapy*** : experimental, gene, therapy, child;
4. ***Experimental gene therapy*** : gene, therapy, experimental, mRNA, Pfizer, government;
5. ***Depopulation*** and ***Bill Gates*** : depopulation, Gates, Bill, poison;
6. ***Experimental gene therapy*** : experimental, gene, therapy, Pfizer, research;
7. ***Experimental therapy*** and ***Freedom and force*** : experimental, free, force;
8. ***Experimental gene therapy*** : experimental, Pfizer, gene, therapy, death, vaccinate, Moderna;
9. ***Bioweapon and Depopulation*** : bioweapon, therapy, gene, depopulation, immunity, herd;

# Non-Misinformation Topics



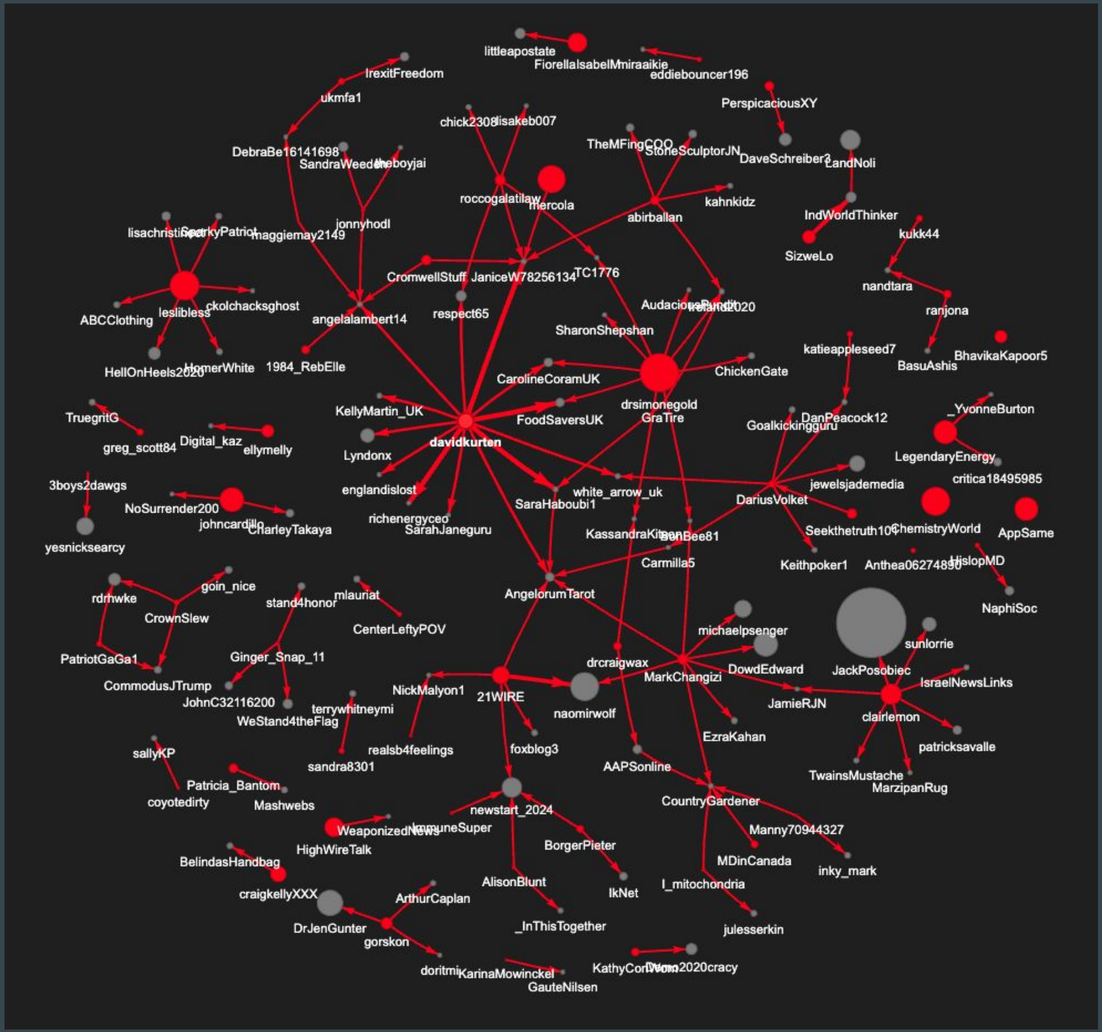

1. ***Got the shot*** : got, first, dose, second, today, shot;
2. ***Vaccinated and grateful*** : vaccinated, grateful, thank, vaccination;
3. ***Worry and excitement*** : worry, excited, parent, appointment;
4. ***Worry*** : *worry, need, ever, vaccination, drink*
5. ***Worry and Mask*** : worry, ever, need, wear mask, social

# Network Analysis: Methodology

- Rank all misinformers based on *misinformation impact*:
    - Direct impact:
        - Number of misinformation tweets × Number of followers
    - Indirect impact:
        - Number of retweeter's follower count for each retweet.
- Build a network of
    - the most impactful misinformers
    - their retweeters (as long as they have more than 10,000 followers)

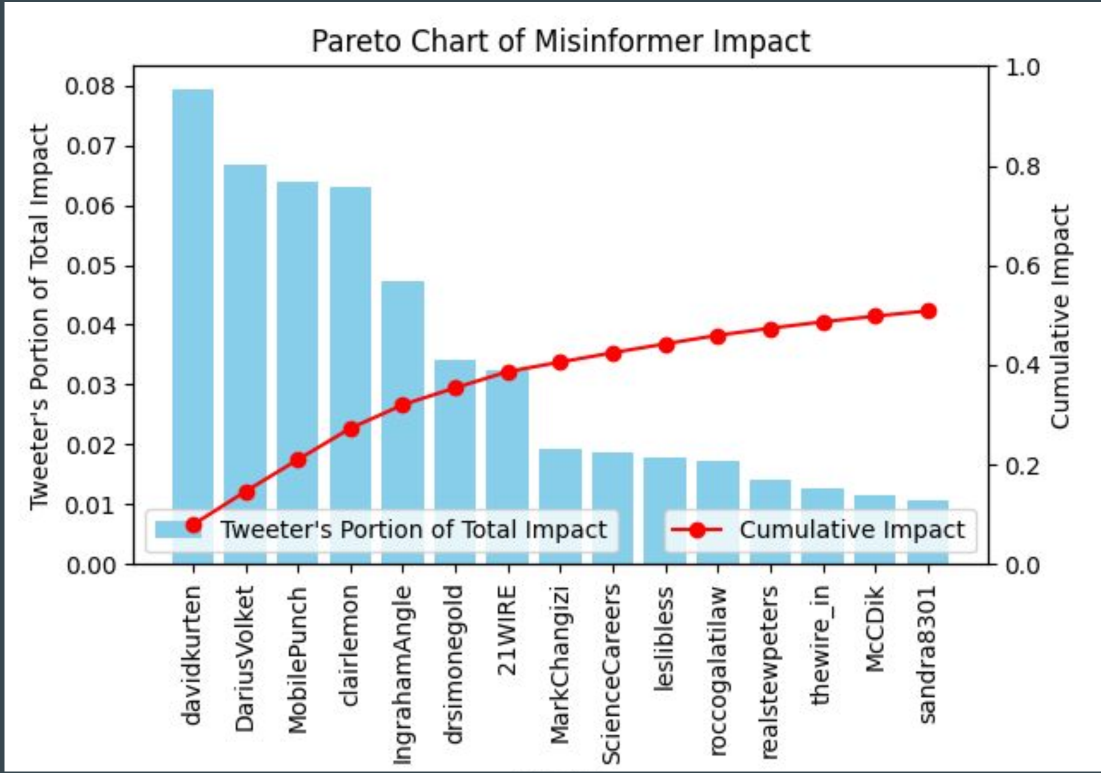
# Network Analysis: Graph

- Different ways of having impact:
  - have many followers
  - be retweeted often



# Network Analysis: Pareto Chart

- 15 misinformers together account for 50% av all misinformation impact.



# Discussion: Data

- Publicly-shared sets of tweets may only contain the tweet ID.
- You have to download the tweet text from X.
- Not all tweets are still available.
- Hayawi et al.
  - Three years since they created the labeled misinformation dataset.
  - Today, only 72% of the tweets are still accessible.
- Makes it impossible to fully reproduce other researchers' work.

# Discussion: Reproducing Classifiers

- The reproduced classifiers did not achieve the same performance as reported in the papers:
    - Misinformation classifier
        - My test-set F1-score: 0.935.
        - Reported by Hayawi et al: 0.98
    - Vaccine hesitancy classifier
        - My test-set accuracy: 75.4%.
        - Reported by Cotfas et al: 95.57%
- Why this deterioration in performance?
    - Less data to train on, due to X's user policy.
    - Other reasons?

# Conclusion

- Topics in misinformation tweets include:
  - *Experimental gene therapy*
  - *Bioweapon and depopulation*
  - *Freedom and force*
- Topics in *non*-misinformation tweets include:
  - *Got the shot*
  - *Vaccinated and grateful*
  - *Worry (and excitement)*
- Network analysis showed:
  - how main misinformers are connected through retweeting
  - The top 15 misinformers are responsible for over 50% of the misinformation impact.

# Future Work

- Develop a reliable vaccine misinformation classifier.
- Use it to extract a much larger set of misinformation tweets.
- Conduct topic modeling on interesting subsets:
    - e.g. *non*-misinformation tweets with a negative vaccination stance.
- Build a network based on larger number of retweets.
    - Would make the analysis more robust.

# References


1. Mellis, C.; Lives saved by COVID-19 vaccines. Journal of Paediatrics and Child Health. 20 September 20122
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3. Cotfas, L.-A.; Craciun, L.; Delcea, C.; Florescu, M.S.; Kovacs, E.-R.; Molanescu, A.G.; Orzan, M. Unveiling Vaccine Hesitancy on Twitter: Analyzing Trends and Reasons during the Emergence of COVID-19 Delta and Omicron Variants. Vaccines 2023, 11, 1381. https://doi.org/10.3390/vaccines11081381