Studying Risk and Crisis Communication during Emerging Infectious Disease Outbreaks from Social Media Big Data

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Emerging Infectious Diseases (EIDs)

- newly identified species of pathogens (such as Zika virus, COVID-19)
- pathogens affecting a new population (e.g., West Nile virus, bird flu, swine flu, SARS)
- drug-resistant bacteria
- reemerging infections (e.g., Measles and drug resistant TB)

EIDs and Social Media

- Theoretical Approaches
  - Risk Communication (How do public health agencies use social media to communicate EID-related information to the public?)
  - Information seeking and information sharing (how do social media users access, process, and share information?)
  - Misinformation (How are the public exposed to misinformation on social media?)

Using Social Media for Crisis and Risk Communication

Tang, L., Liu, W., Thomas, B., Tran, M., Zou, W., Zhang, X., & Zhi, D. (2021). Texas public agencies' tweets and public engagement during the COVID-19 Pandemic: Natural language processing approach. *Journal of Medical Internet Research: Public Health and Surveillance*. 7(4): e26720.

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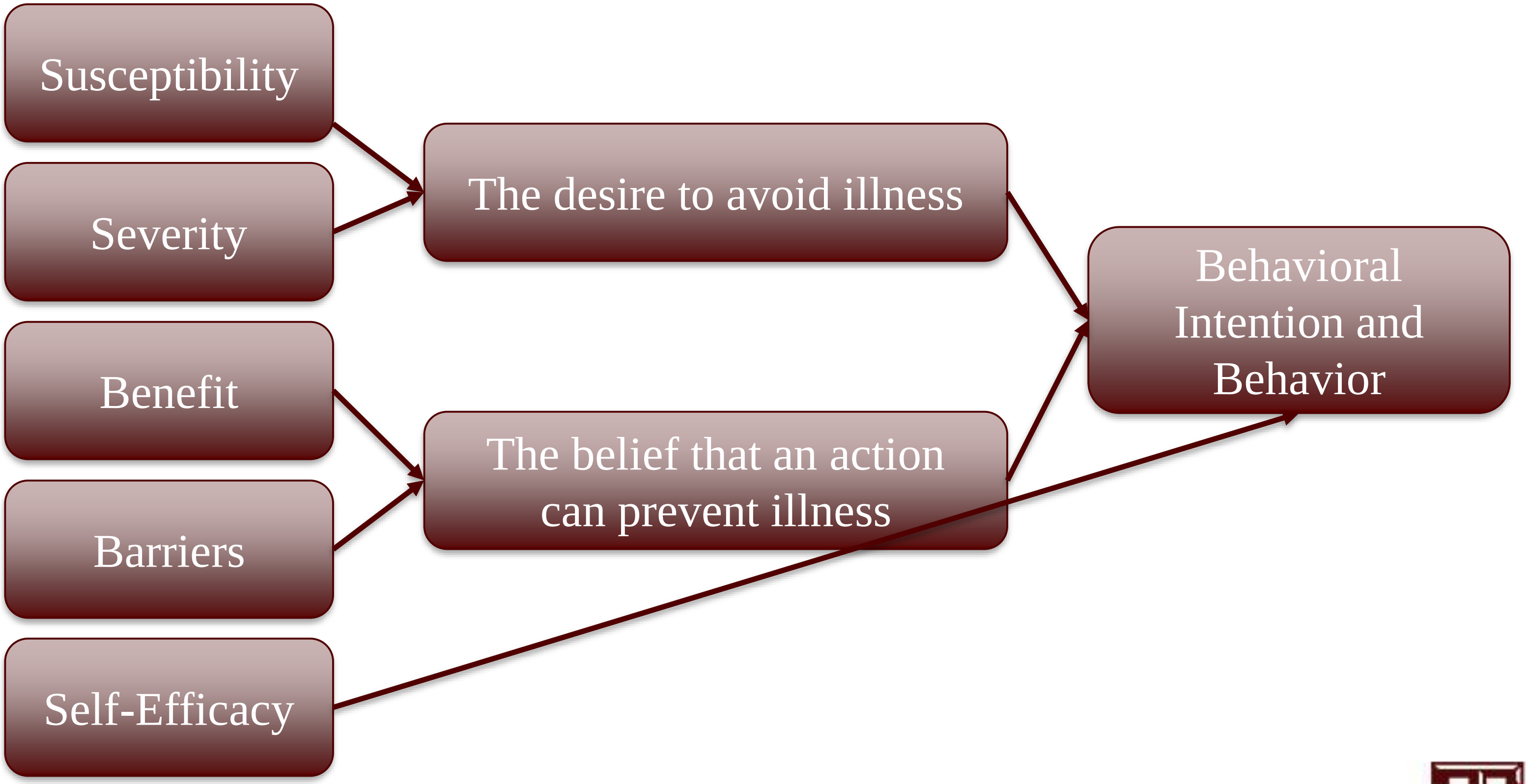
How do public health agencies use social media during EID outbreaks I

- Functions of organizational social media use (Lovejoy & Saxton, 2012)
  - Information
  - Action
  - Community

How do public health agencies use social media during EID outbreaks II

- Health Belief Model



Texas public agencies' tweets and public engagement during the COVID-19 Pandemic: Natural language processing approach.

Collecting tweets (n=15382)

Creating training dataset

Using training data to train algorithm and testing (BERT)

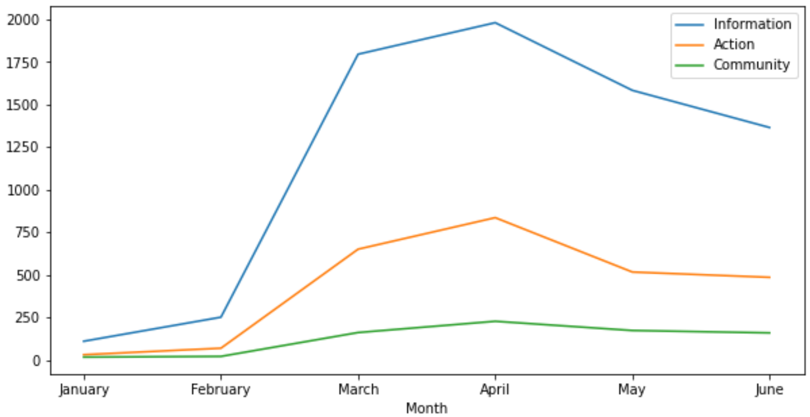
Classifying the big data set

Items to classify:

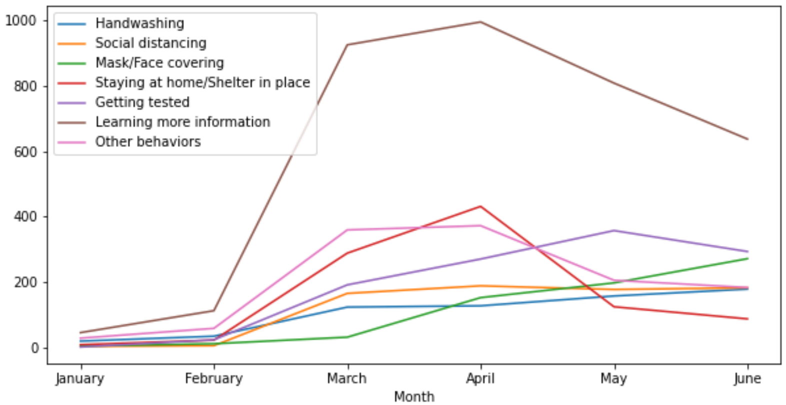
- Types of message: Information, action, community
- Behaviors recommended
- Health Beliefs (from the Health belief Model): severity, susceptibility, benefit, barriers, self efficacy

Results

Types of Message



Behaviors Recommended



Public Engagement

- Features associated with retweeting
  - Information (+) and action (+)
  - Severity (+)and susceptibility (+)
- Features associated with endorsement (Likes)
  - Action (+) and community (+)
  - Severity (+)and susceptibility (+)

How are social media users exposed to vaccine misinformation

Tang, L., Fujimoto, K., Amith, M., Cunningham, R., Costantini, R.A., , York, F., Xiang, G., Boom, J., & Tao, C. (2021). "Down the rabbit hole" of vaccine misinformation on YouTube: Network exposure study. *Journal of Medical Internet Research, 23*(1): e23262.

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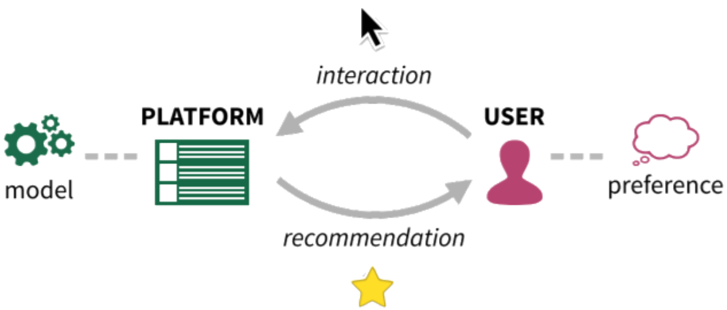
Vaccine Misinformation and YouTube Algorithm

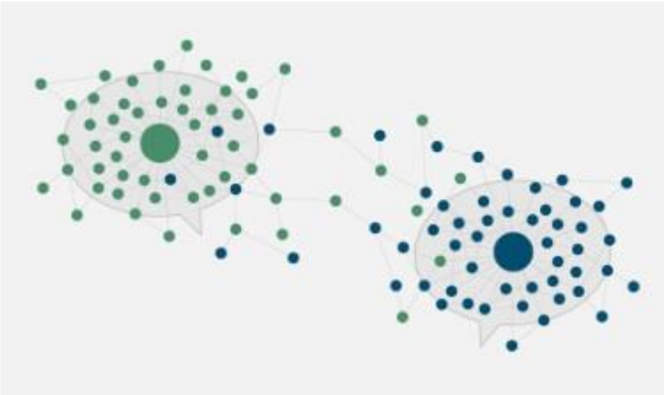
Filter bubbles

- Recommendation algorithm
- Diffusion of information on YouTube



Echo chamber

- Closed groups in the network
- Friends' recommendation

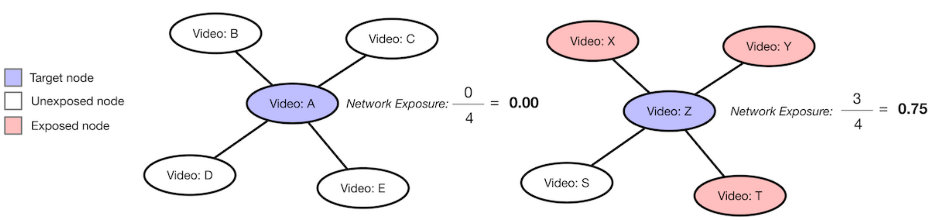


How do we use YouTube?

Goal-oriented browsing (start from keyword-based search)

Direct navigation (start from a seed video on another platform)

The network exposure model measures the degree to which a node in the network is exposed to other nodes with a certain attribute.



- RQ1:When YouTube users start their viewing with provaccine or antivaccine keywords, or an antivaccine seed video, to what extent will they will be exposed to pro- and antivaccine content?
- RQ2: What is the degree of exposure of pro- and antivaccine videos as well as other videos unrelated to vaccines to additional antivaccine videos?

Method

Data Collection

Goal oriented browsing: Based on asset of key words derived from the most popular Twitter hashtag (a list of positive keywords and a list of negative keywords)

Direct navigation: Based on two lists of antivaccine videos (conspiracy theory and antivaccine expert)

First 6 recommended videos, three levels

CAS^{2}T used for data collection

Annotation

815 videos→(remove duplicates)→ 538 videos

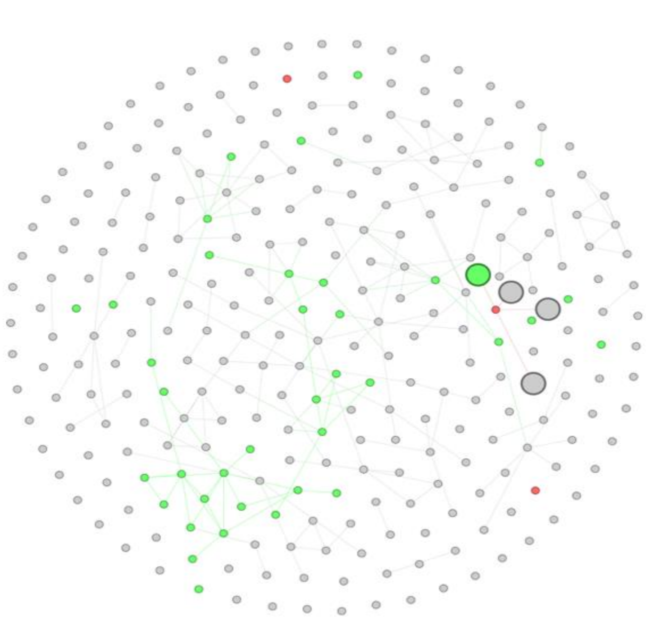
Related to vaccine or not

Unrelated video: is it related to autism? Does it contain health information? Does it contain health misinformation?

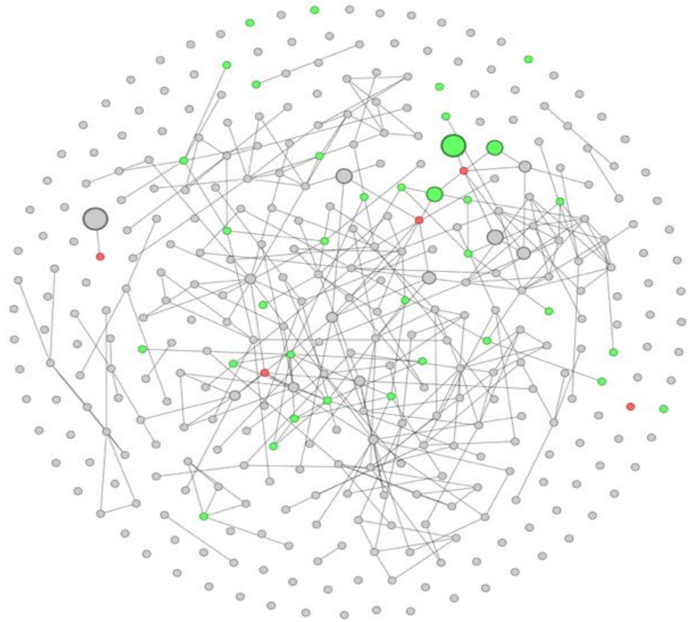
Related video: is it pro or antivaccine?

Sources of video

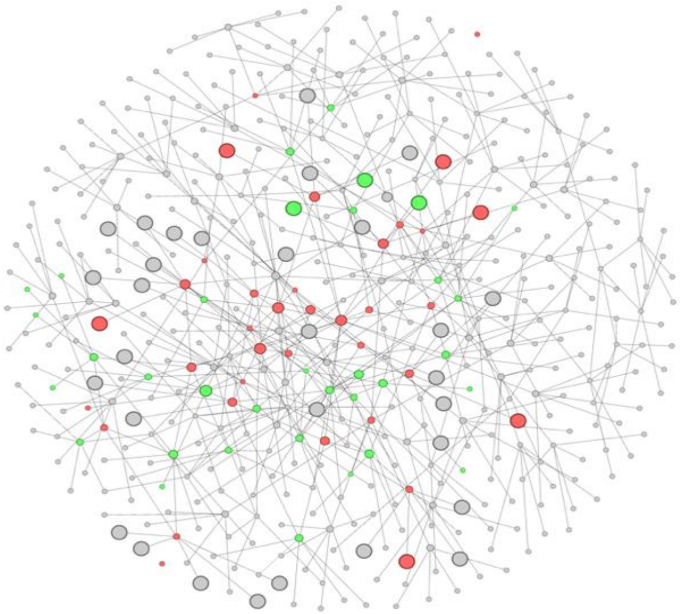
Data analysis



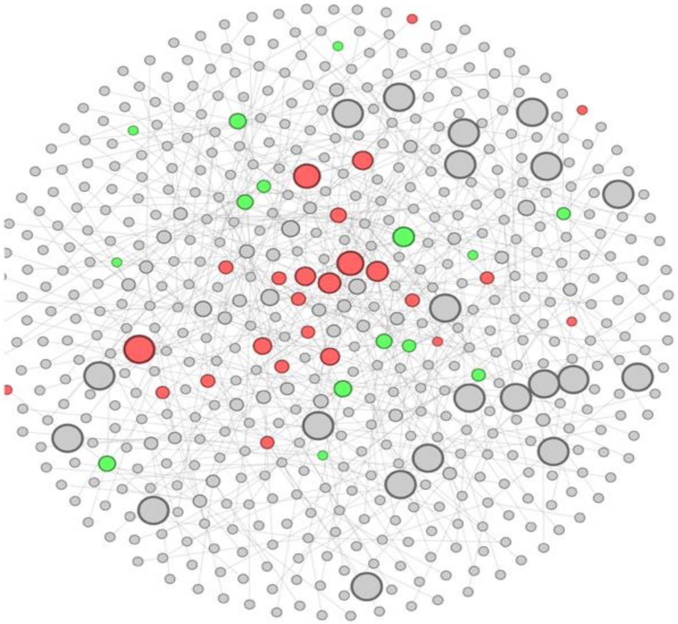
Pro-vaccine search network



Anti-vaccine search network



Vaccine conspiracy seed network



Anti-vaccine expert seed network

RQ1: *When YouTube users start their viewing with pro-vaccine, or anti-vaccine keywords, or an anti-vaccine seed videos, to what extent will YouTube users be exposed to pro and anti-vaccine content?*

	Search Networks		Seed Networks	
	Pro-Vaccine Search Network (n=283)	Anti-Vaccine Search Network (n=354)	Conspiracy Seed Network (n=483)	Anti-Vaccine Expert Seed Network (n=551)
# Vaccine-related	41 (14%)	40 (11%)	70 (14%)	40 (7%)
Pro-vaccine (% wrt vax videos)	38 (93%)	35 (87.5%)	34 (49%)	15 (38%)
Anti-vaccine (% wrt vax videos)	3 (7%)	5 (12.5%)	36 (51%)	25 (63%)
Source of Videos (% with regard to vaccine related videos)				
Government agencies	23 (56%)	14 (35%)	0 (0%)	0 (0%)
Academic institutions and hospitals	6 (15%)	13 (33%)	9 (13%)	1 (3%)
Pharmaceutical companies and for profit organizations	1 (2%)	0 (0%)	1 (1%)	0 (0%)
Consumer generated	3 (7%)	5 (13%)	33 (47%)	26 (65%)
News media	8 (20%)	9 (23%)	27 (39%)	13 (33%)
Professional Associations	0 (0%)	2 (5%)	0 (0%)	0 (0%)
Other	0 (0%)	2 (5%)	0 (0%)	0 (0%)

RQ2: *What is the degree of exposure of pro and anti-vaccine videos as well as other videos unrelated to vaccines to additional anti-vaccine video?*

	Search Networks		Seed Networks	
	Pro-Vaccine Search Network	Anti-Vaccine Search Network	Conspiracy Seed Network	Anti-Vaccine Expert Seed Network
Average Anti-vaccine Exposure				
Mean (SD)	0.01 (0.12)	0.02 (0.10)	0.12 (0.28)	0.07 (0.21)
Min < Max	1	0.11 < 1	0.13<1	0.13<1
# of nodes exposed	4 (1.4%)	15 (4.2%)	119 (24.7%)	86 (15.6%)
# of nodes unexposed	279 (98.6%)	339 (95.8%)	364 (75.3%)	465 (84.4%)
Anti-vaccine Exposure (odds ratios)				
non-vaccine video (CI 95%)	0.50 (CI: 0.04, 27.0)	0.48 (CI: 0.12, 2.8)	0.07 (CI: 0.04, 0.14)	0.4 (CI: 0.02, 0.09)
vaccine video (CI 95%)	1.99 (CI: 0.04, 25.0)	2.1 (CI: 0.36, 8.3)	13.6* (CI: 7.3, 25.9)	24.4* (CI: 10.8, 58.4)
pro-vaccine video (CI 95%)	2.18 (CI: 0.04, 27.9)	2.4 (CI: 0.41, 9.5)	8.94* (CI: 3.9, 21.6)	12.1*(CI: 3.6, 46.1)
anti-vaccine videos (CI 95%)	0.00 (CI: 0, 108.7±)	0.00 (CI: 0.0, 18.1±)	11.6* (CI: 5.0, 28.8)	27.9*(CI: 9.6, 97.3)
autism videos (CI 95%)	0.00 (CI: 0, 50.3±)	0.00 (CI: 0.0, 4.0±)	0.92 (CI: 0.16, 3.6)	2.1(CI: 0.65, 5.9)
health videos (CI 95%)	5.62(CI: 0.44, 297)	0.00 (CI: 0.0, 0.36±)	1.52 (CI: 0.98, 2.4)	2.0* (CI: 1.2, 3.5)
accurate health information (CI 95%)	5.71(CI: 0.45, 301.8)	0.00 (CI: 0.0, 0.37±)	0.97 (CI: 0.60, 1.5)	1.22(CI: 0.72, 2.0)
health misinformation (CI 95%)	0.00	0.00 (CI: 0.0, 30.6±)	1.80* (CI: 1.1, 2.9)	1.76* (CI: 1.0, 2.9)

How about a different language and cultural context?

Statistics	Search networks		Seed networks	
	Pro-vaccine search terms	Anti-vaccine search terms	Conspiracy videos network	Expert videos network
Mean (SD)	0.035 (0.18)	0.048 (0.215)	0.037 (0.190)	0.083 (0.277)
Range	0.67	0.33	0.17	0.33
Nodes Exposed, n (%)	11 (3.5)	14 (4.8)	8 (3.7)	12 (8.3)
Nodes unexposed, n (%)	304 (96.5)	276 (95.2)	206 (96.3)	132 (91.7)
Odds ratio (95% CI)				
Nonvaccine video	0.30 (0.01- 2.11)	3.71(0.42-44.98)	4.90 (0.54-59.63)	8.37 (2.23-34.22)
Vaccine video	0.32 (0.01-2.28)	4.60 (0.51-55.83)	6.75 (0.74-82.34)	3.69 (0.86-13.96)
Pro-vaccine video	0.36 (0.01-2.58)	1.23 (0.25-12.82)	2.82(0.54-30.52)	0.64 (0.01-4.92)
Anti-vaccine video	0 (0-8.94)[a]	0 (0-15.88)[a]	7.21 (0.13-85.49)	6.1 (1.12-27.63)
Mixed vaccine messages video	1.28 (0.28-9.71)	0(0-18.83)[a]	6.28 (0.11-72.90)	0 (0-12.50)[a]
Neutral vaccine video	0.45 (0.01-3.22)	6.27 (0.69-76.10)	7.46 (0.81-91.03)	9.92 (0.12-784.56)
Health Related	0.56 (0.01-4.08)	5.29 (0.59-64.08)	1.93(0.04-20.48)	8.86 (2.32-34.42)
Covid Related	0.27 (.01-1.93)	4.36 (0.49-52.78)	6.54 (0.72-79.74)	5.8 (1.53-21.69)

Identifying Vaccine Adverse Events from Social Media Data

Lian, A., Du, J., & **Tang, L.** (2022) Using a machine learning approach to monitor COVID-19 vaccine adverse events (VAE) from Twitter data. *Vaccines, 10*(1):103.

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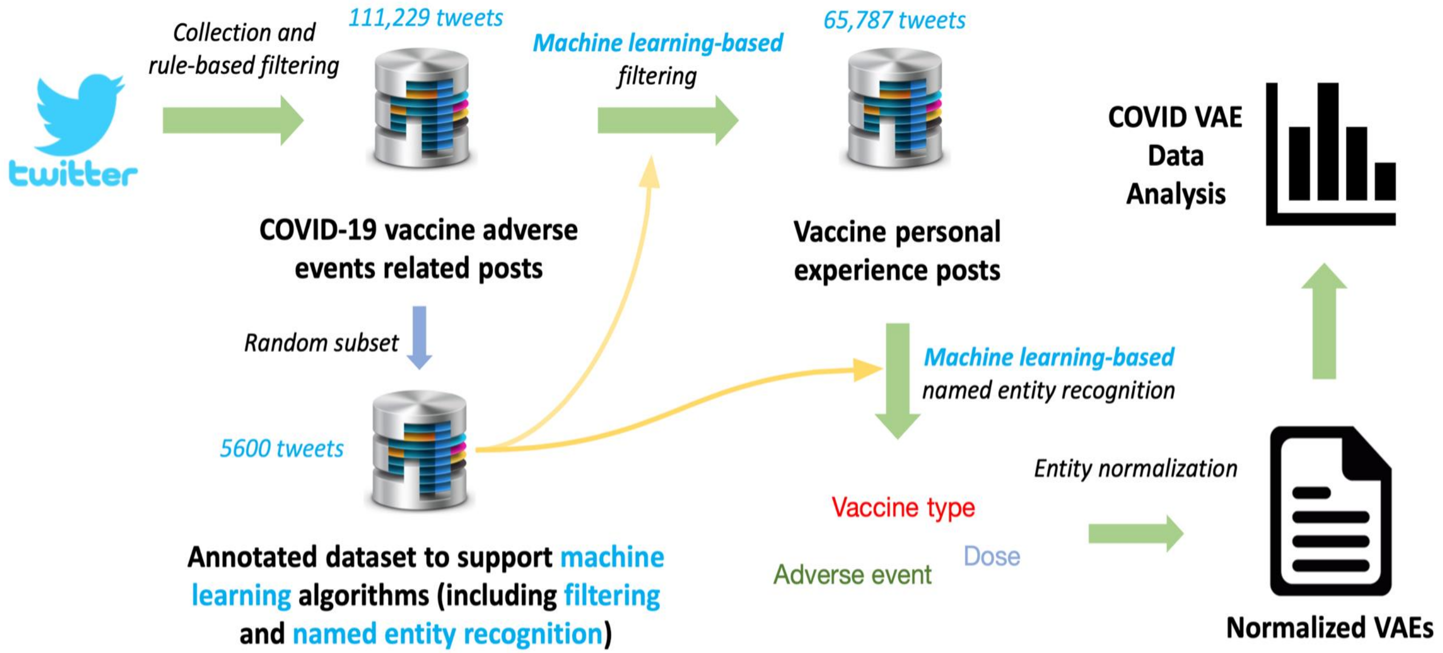
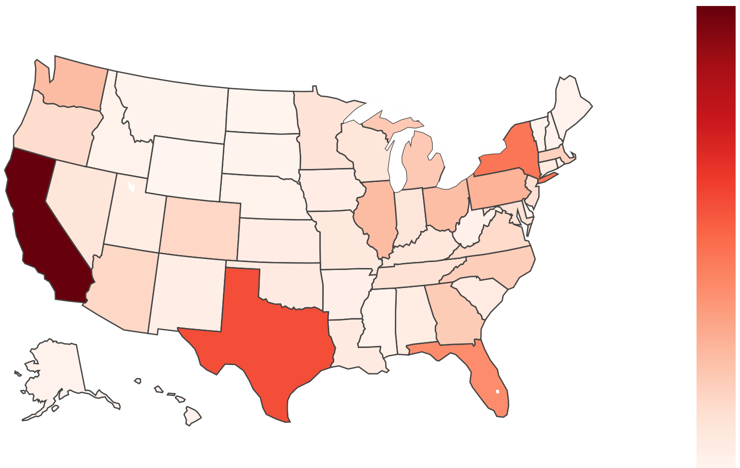
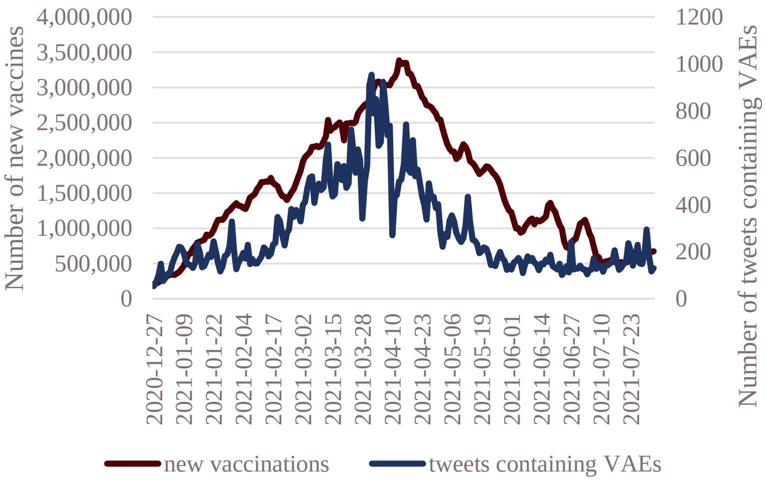
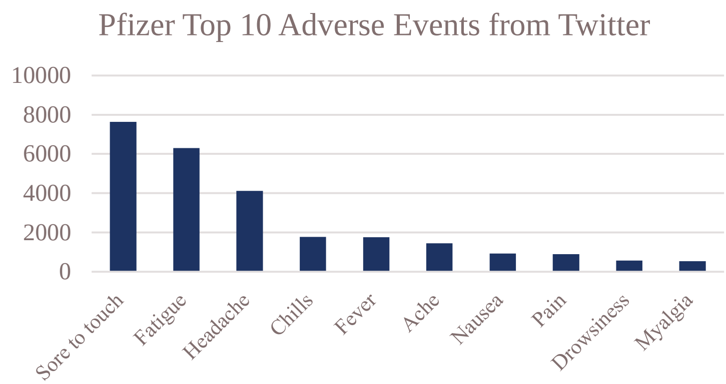
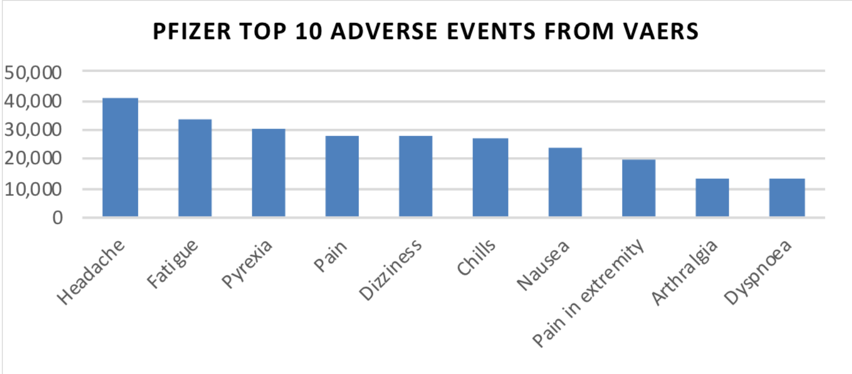


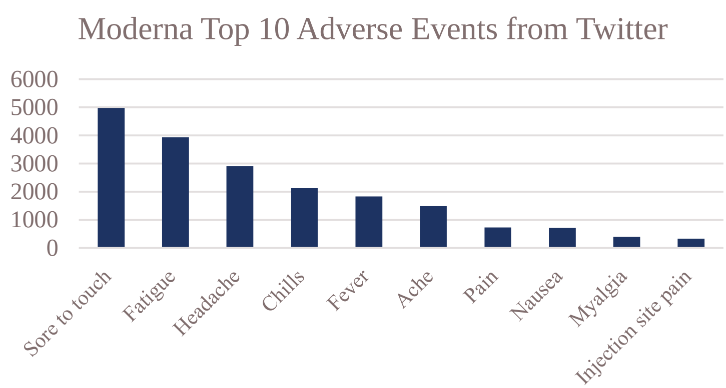
Collection and rule-based filtering
111,229 tweets
Machine learning-based filtering
65,787 tweets
COVID VAE Data Analysis
COVID-19 vaccine adverse events related posts
Vaccine personal experience posts
Random subset
Machine learning-based named entity recognition
5600 tweets
Entity normalization
Vaccine type
Dose
Adverse event
Annotated dataset to support machine learning algorithms (including filtering and named entity recognition)
Normalized VAEs

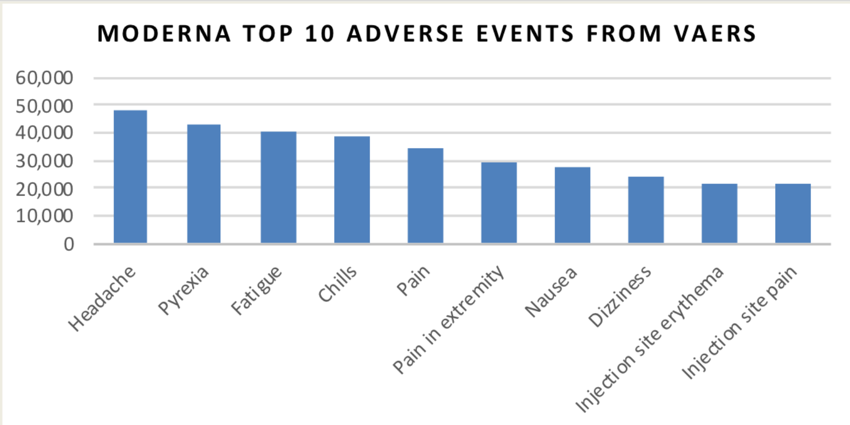

3000
2500
2000
1500
1000
500

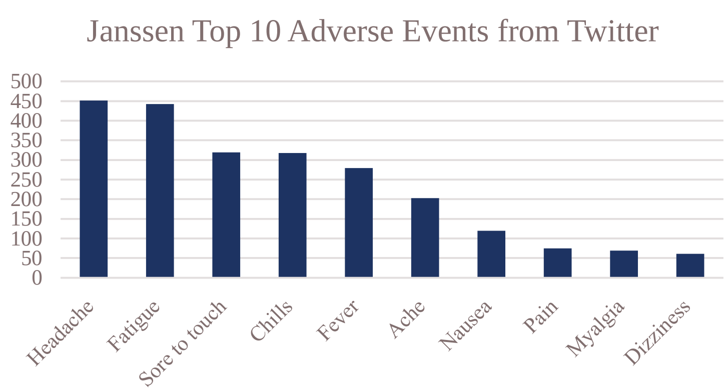

Number of new vaccines
4,000,000
3,500,000
3,000,000
2,500,000
2,000,000
1,500,000
1,000,000
500,000
0
Number of tweets containing VAEs
1200
1000
800
600
400
200
0
2020-12-27
2021-01-09
2021-01-22
2021-02-04
2021-02-17
2021-03-02
2021-03-15
2021-03-28
2021-04-10
2021-04-23
2021-05-06
2021-05-19
2021-06-01
2021-06-14
2021-06-27
2021-07-10
2021-07-23
new vaccinations
tweets containing VAEs

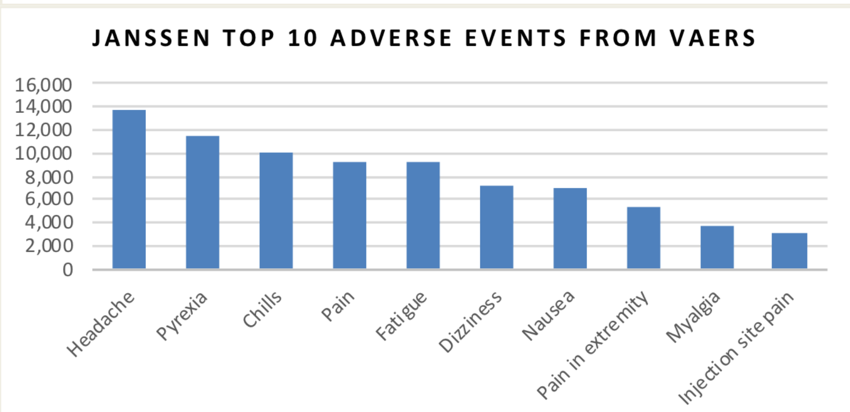

Pfizer Top 10 Adverse Events from Twitter
10000
8000
6000
4000
2000
0
Sore to touch
Fatigue
Headache
Chills
Fever
Ache
Nausea
Pain
Drowsiness
Myalgia


PFIZER TOP 10 ADVERSE EVENTS FROM VAERS
50,000
40,000
30,000
20,000
10,000
0
Headache
Fatigue
Pyrexia
Pain
Dizziness
Chills
Nausea
Pain in extremity
Arthralgia
Dyspnoea


Moderna Top 10 Adverse Events from Twitter
6000
5000
4000
3000
2000
1000
0
Sore to touch
Fatigue
Headache
Chills
Fever
Ache
Pain
Nausea
Myalgia
Injection site pain


MODERNA TOP 10 ADVERSE EVENTS FROM VAERS
60,000
50,000
40,000
30,000
20,000
10,000
0
Headache
Pyrexia
Fatigue
Chills
Pain
Pain in extremity
Nausea
Dizziness
Injection site erythema
Injection site pain


Janssen Top 10 Adverse Events from Twitter
500
450
400
350
300
250
200
150
100
50
0
Headache
Fatigue
Sore to touch
Chills
Fever
Ache
Nausea
Pain
Myalgia
Dizziness


JANSSEN TOP 10 ADVERSE EVENTS FROM VAERS
16,000
14,000
12,000
10,000
8,000
6,000
4,000
2,000
0
Headache
Pyrexia
Chills
Pain
Fatigue
Dizziness
Nausea
Pain in extremity
Myalgia
Injection site pain

THANK YOU! QUESTIONS?