SUPPLEMENTARY MATERIALS

Materials and Methods

Rationale for choosing the 20 global health actors

1. Hoffman & Cole (2018), Frenk & Moon (2013), and Szlezak et al. (2010) were the basis for the 20 global health actors in this study.[4, 15, 16]
   a. Hoffman & Cole (2018) used the related search function in Google in order to systematically map global health actors – 20 global health actors were identified as most important based on their methodology and was validated by 9 identified global health experts.
   b. Frenk & Moon (2013) identifies 9 primary types of actors in global health with 24 examples in their study on pluralism and other challenges in global health.
   c. Zlezak et al. (2010) describes their 8 identified types of actors in global health as a partnership in their article that argues for the norms and roles of each actor in the transition of global health.
2. The identified global health actors across the 3 studies were compared, and the 20 actors that were identified most important by all 3 studies were chosen.

Collection of tweets

1. Twitter is one of the social media platforms where global health actors actively and consistently share their work, research, and news to the general global public.
2. Using the Twitter Application Programming Interface (API), tweets from of the 20 global health actors were collected from November 2016 to May 2020 in three month intervals.
   a. All the tweets of each of the 20 global health actors were collected for the following 15 months:
      i. 2016: November
      ii. 2017: February, May, August, November
      iii. 2018: February, May, August, November
      iv. 2019: February, May, August, November
      v. 2020: February, May
   b. November 2019 is the identified beginning of the COVID-19 outbreak.
   c. This scope allows an analysis of tweets of global health actors 3 years leading up to the COVID-19 outbreak and 6-months into the pandemic.
3. Three month intervals were chosen with the assumption that a variance in the issues, topics, and themes that global health actors tweet can be seen in three month intervals while allowing for efficient usage of the request limit from the Twitter API.

Topic modelling

1. Topic Modeling was conducted to identify the 10 most tweeted global health issues/topics by each actor in each of the 15 months in the study.

2. The 10 most tweeted global health issues/topics were used to describe the set of issues/problems a specific global health actor prioritizes in a given month.
3. Latent Dirichlet Allocation (LDA) was used in topic modeling.
4. Topic modeling answers the questions:
    a. "What are the most prioritized issues among the identified global health actors from 2016 to 2020?"
    b. "When did global health actors have pandemic preparedness as a priority in the three years leading up to the COVID-19 pandemic?"
    c. "What are the trends in prioritization of global health issues between and among different types of global health actors?

FAQs about how LDA was used in this study

- What did the authors do with tweets that mentioned both "breastfeeding" and "mothers"? Do the authors believe that the revealed priorities of an organization that references both breastfeeding and mothers are substantively different than those of an organization that just references breastfeeding, and so on?
    - For context, LDA topic modeling is a form of "unsupervised machine learning" where the data used is "unlabeled." This means that when we ran the algorithm, we did not define what statements will be categorized as "breastfeeding" and what will be categorized as "mothers." We also did not define what words would fall under any other topics that were generated by the model. The only input from us is was how many topics we want the LDA algorithm to categorize the corpus of text. In our analysis, we generated 10 topics for each of the 20 actors. The LDA algorithm generates topics based on a generative probabilistic model that assumes each topic is a mixture over an underlying set of words, and each corpus of text is a mixture of sets of topic probabilities. In a nutshell, the algorithm analyzes all the words in all the tweets of a specific actor. It then generates probabilities of each unique word appearing with other words in a certain tweet or sentence. Topics are then generated by the model based on these sets of probabilities.
- Some topics are quite general (e.g., "Poverty", "Treatment", "News"), while others are more specific ("Fisheries", "Hepatitis", "Veterans"). In cases where one topic could be subsumed by another (e.g., "Schools" could be subsumed by "Education"), how did the authors disaggregate these?
    - We did not have any input in categorizing any of the topics generated. The topics generated are based on the words and language used by each respective actor in their tweets. The algorithm uses the words/language used by the actor in their tweets to generate topics. We did not make any other edits to the topics after they were generated.

Code for collecting tweets

```
# CREDENTIALS
import yaml

config = dict(
    search_tweets_api = dict(
        account_type = 'premium',
        endpoint = 'https://api.twitter.com/1.1/tweets/search/fullarchive/datacollection.json',
```

```
        consumer_key = 'xxxxxxxxxxxxxxxxxxxxxxxxxxxxxx',
        consumer_secret = 'xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx'
    )
)

with open('twitter_keys_fullarchive.yaml', 'w') as config_file:
    yaml.dump(config, config_file, default_flow_style=False)

# LOAD CREDENTIALS
from searchtweets import load_credentials

premium_search_args = load_credentials("twitter_keys_fullarchive.yaml",
                                       yaml_key="search_tweets_api",
                                       env_overwrite=False)
print(premium_search_args)

# QUERY RULE SET UP
from searchtweets import gen_rule_payload

rule = gen_rule_payload("from:username",
                        results_per_call=500,
                        from_date="2020-02-01",
                        to_date="2020-03-01"
                       )

# WRITE TO JSONL config_file
import json

with open('tweets_feb_2020.jsonl', 'a', encoding='utf-8') as f:
    n = 0
    for tweet in rs.stream():
        n += 1
        if n % 10 == 0:
            print('{0}: {1}'.format(str(n), tweet['created_at']))
        json.dump(tweet, f)
        f.write('\n')
print('done')
```

REPEAT FOR OTHER USERS AND MONTHS

Code for topic modelling

```
# Importing modules

import pandas as pd

# Read data into tweets_df
tweets_df = pd.read_csv('tweets_nov2016-may2020.csv')

# Print head
tweets.head()

# Remove the columns
tweets_df = tweets_df[["username","user_id","created_at","tweet"]]

# Print out the first rows of tweets_df
tweets_df.head()

# Create dataframe for each month in analysis
tweets_feb = tweets.loc[tweets.created_at.str.contains("Feb")]
tweets_feb_17 = tweets_feb.loc[tweets_feb.created_at.str.contains("2017")]
tweets_feb_18 = tweets_feb.loc[tweets_feb.created_at.str.contains("2018")]
tweets_feb_19 = tweets_feb.loc[tweets_feb.created_at.str.contains("2019")]
tweets_feb_20 = tweets_feb.loc[tweets_feb.created_at.str.contains("2020")]

tweets_may = tweets.loc[tweets.created_at.str.contains("May")]
tweets_may_17 = tweets_may.loc[tweets_may.created_at.str.contains("2017")]
tweets_may_18 = tweets_may.loc[tweets_may.created_at.str.contains("2018")]
tweets_may_19 = tweets_may.loc[tweets_may.created_at.str.contains("2019")]
tweets_may_20 = tweets_may.loc[tweets_may.created_at.str.contains("2020")]

tweets_aug = tweets.loc[tweets.created_at.str.contains("Aug")]
tweets_aug_17 = tweets_aug.loc[tweets_aug.created_at.str.contains("2017")]
tweets_aug_18 = tweets_aug.loc[tweets_aug.created_at.str.contains("2018")]
tweets_aug_19 = tweets_aug.loc[tweets_aug.created_at.str.contains("2019")]
```

```
tweets_nov = tweets.loc[tweets.created_at.str.contains("Nov")]
tweets_nov_16 = tweets_nov.loc[tweets_nov.created_at.str.contains("2016")]
tweets_nov_17 = tweets_nov.loc[tweets_nov.created_at.str.contains("2017")]
tweets_nov_18 = tweets_nov.loc[tweets_nov.created_at.str.contains("2018")]
tweets_nov_19 = tweets_nov.loc[tweets_nov.created_at.str.contains("2019")]

# Helper function
def plot_10_most_common_words(count_data, count_vectorizer):
    import matplotlib.pyplot as plt
    words = count_vectorizer.get_feature_names()
    total_counts = np.zeros(len(words))
    for t in count_data:
        total_counts+=t.toarray()[0]

    count_dict = (zip(words, total_counts))
    count_dict = sorted(count_dict, key=lambda x:x[1], reverse=True)[1:23]
    words = [w[0] for w in count_dict]
    counts = [w[1] for w in count_dict]
    x_pos = np.arange(len(words))

    plt.figure(2, figsize=(15, 2))
    plt.subplot(title=f'10 Most Common Words')
    sns.set_context("notebook", font_scale=1.25, rc={"lines.linewidth": 2.5})
    sns.barplot(x_pos, counts, palette='husl')
    plt.xticks(x_pos, words, rotation=90)
    plt.xlabel('words')
    plt.ylabel('counts')
    plt.show()

# Import Libraries
from sklearn.feature_extraction.text import CountVectorizer
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns

import re
import string

# Identify top 10 keywords, issues, topics of each actor for a given month
tweets = tweets_nov_16[tweets_nov_16["username"] == username]
tweets = tweets_df[tweets_df['username'].isin(username)]
printable = set(string.printable)
tweets['paper_text_processed'] = tweets['tweet'].map(lambda x: re.sub('[,\.!?]', '', x))
tweets['paper_text_processed'] = tweets['tweet'].map(lambda x: x.encode('ascii','ignore'))
exclusionList = ['amp','https','RT','people','know','living','new','2018','latest','use', 'week',
                 'ECDC_EU','thank','Thank','DYK','USAID','today','world','million','country',
                'foreignoffice','UK','billgates','melindagates','2019','des','33', 'DFID',
                '000','day','like','year','old','live','UNITAID','PATHtweets','PATH','para',
                'WorldBank','LIVE','WHOAFRO','WHOWPRO','WHOSEARO','WHOEMRO','GlobalFund','WHO_Europe','la'
                ]
exclusions = '|'.join(exclusionList)
tweets['paper_text_processed'] = tweets['tweet'].map(lambda x: re.sub(exclusions, '', x))
tweets['paper_text_processed'] = tweets['paper_text_processed'].map(lambda x: x.lower())
tweets['paper_text_processed'].head()
sns.set_style('whitegrid')
%matplotlib inline
count_vectorizer = CountVectorizer(stop_words='english')
count_data = count_vectorizer.fit_transform(tweets['paper_text_processed'])
import warnings
warnings.simplefilter("ignore")
plot_10_most_common_words(count_data, count_vectorizer)

# LDA Topic Modeling
import warnings
warnings.simplefilter("ignore", DeprecationWarning)
# Load the LDA model from sk-learn
from sklearn.decomposition import LatentDirichletAllocation as LDA

# Helper function
def print_topics(model, count_vectorizer, n_top_words):
    words = count_vectorizer.get_feature_names()
    for topic_idx, topic in enumerate(model.components_):
        print("\nTopic #%d:" % topic_idx)
        print(" ".join([words[i]
                        for i in topic.argsort()[:-n_top_words - 1:-1]]))

# Tweak the two parameters below
number_topics = 5
```

```
number_words = 10
# Create and fit the LDA model
lda = LDA(n_components=number_topics, n_jobs=-1)
lda.fit(count_data)
# Print the topics found by the LDA model
print("Topics found via LDA:")
print_topics(lda, count_vectorizer, number_words)
```

How network maps were analyzed

- **What is network analysis?** Network analysis is an analytic method that has proved to be useful in understanding relational dynamics across actors in global and public health. (Lopreite et al. 2021 and Quisell et al. 2018).
- **Why use network analysis for the study?** Network analysis was conducted to observe the funding relationships between global health actors.
- **What tool was used?** Gephi 0.9.2 was used in constructing and analyzing the network map.
- **How was the network map designed?**
    - The network modelled in the study allows for a graphical visualization of the flows of global health funding in 2019.
    - The network map was designed such that each global health actor is represented by a node and lines or “edges” indicate a flow of funding in global health.
    - The Fruchterman-Reingold algorithm was used in modelling the network map.
        - The algorithm “calculates the optimal layout so that nodes with less strength and less connections are placed further apart, and those with more and/or stronger connections are placed closer to each other.”[18]
        - The thickness of edges represents the amount of funding transferred between actors.
        - The modelled network map can be found and will be discussed in the findings section.

DAH funding data network analysis summary statistics

Network Overview		
Average Degree	25.403	Run
Avg. Weighted Degree	254.124	Run
Network Diameter	4	Run
Graph Density	0.113	Run
HITS		Run
Modularity	0.093	Run
PageRank		Run
Connected Components	1	Run

Twitter data network analysis summary statistics

Network Overview			
Average Degree	2.181	Run	ⓘ
Avg. Weighted Degree	4.614	Run	ⓘ
Network Diameter	3	Run	ⓘ
Graph Density	0.027	Run	ⓘ
HITS		Run	ⓘ
Modularity	0.172	Run	ⓘ
PageRank		Run	ⓘ
Connected Components	14	Run	ⓘ

DAH funding data network analysis statistics report

	Label	indegree	outdegree	Degree	weighted indegree	weighted outdegree	Weighted Degree	Eccentricity	closnesscentrality	harmonicclosnesscentrality	betweenesscentrality	modularity_class	strongcompnum
African Development Bank		25	57	82	1149	1149	2298	1	1.00	1.00	54.18	1	57
Asian Development Bank		26	48	74	723	723	1446	3	0.42	0.53	52.20	0	160
United Arab Emirates		1	79	80	79	79	158	1	1.00	1.00	7.28	2	161
Australia		1	151	152	137	1021	1158	2	0.85	0.91	0.00	2	175
Austria		1	128	129	112	1083	1195	2	0.76	0.85	0.00	0	179
Belgium		1	140	141	123	1278	1401	2	0.80	0.87	0.00	0	181
Canada		1	163	164	146	1564	1710	2	0.89	0.94	0.00	2	183
Switzerland		1	138	139	124	866	990	2	0.82	0.89	0.00	2	184
China		39	12	51	251	380	631	2	0.52	0.53	661.00	1	160
Germany		1	165	166	147	1476	1623	2	0.90	0.94	0.00	0	185
Denmark		1	131	132	115	1229	1344	2	0.77	0.85	0.00	0	186
Spain		1	152	153	134	1498	1632	2	0.84	0.91	0.00	0	188
Finland		1	160	161	144	1210	1354	2	0.88	0.93	0.00	0	189
France		1	172	173	154	1466	1620	2	0.92	0.96	0.00	0	192
United Kingdom		1	168	169	150	1552	1702	2	0.91	0.95	0.00	0	193
Greece		1	148	149	133	1031	1164	2	0.83	0.90	0.00	0	194
Ireland		1	120	121	104	1081	1185	2	0.74	0.82	0.00	2	195
Italy		1	160	161	143	1433	1576	2	0.88	0.93	0.00	0	196
Japan		1	169	170	155	1111	1266	2	0.94	0.97	0.00	2	198
Korea		1	138	139	125	876	1001	2	0.82	0.89	0.00	2	199
Luxembourg		1	130	131	114	1124	1238	2	0.77	0.85	0.00	2	200

Netherlands	1	158	159	142	1380	1522	2	0.87	0.93	0.00	0	201
Norway	1	157	158	138	1221	1359	2	0.86	0.92	0.00	2	203
New Zealand	1	129	130	118	633	751	2	0.78	0.86	0.00	3	204
Portugal	1	73	74	57	885	942	3	0.62	0.69	0.00	0	205
Sweden	1	155	156	139	1464	1603	2	0.86	0.92	0.00	0	206
United States	1	165	166	150	1390	1540	2	0.92	0.96	0.00	2	207
Bill & Melinda Gates Foundation	1	162	163	146	1280	1426	2	0.89	0.94	0.00	1	208
Coalition for Epidemic Preparedness Innovations	10	1	11	10	10	20	1	1.00	1.00	0.23	1	163
European Commission	15	148	163	2184	2184	4368	3	0.83	0.92	53.93	0	178
European Economic Area	3	7	10	17	17	34	1	1.00	1.00	8.85	2	202
Gavi	28	118	146	2024	2024	4048	3	0.65	0.81	110.05	1	160
Global Fund	29	155	184	4119	4119	8238	3	0.91	0.96	336.01	2	160
Inter-American Development Bank	15	34	49	269	269	538	1	1.00	1.00	49.50	2	119
International NGOs	27	151	178	2323	2323	4646	3	0.86	0.94	198.03	2	171
US NGOs	27	158	185	442	442	884	3	0.90	0.95	306.65	1	174
Pan American Health Organization	23	44	67	318	318	636	3	0.41	0.52	28.46	2	162
UNAIDS	30	133	163	612	612	1224	3	0.73	0.87	198.05	1	160
UNFPA	30	141	171	1630	1630	3260	3	0.79	0.90	226.79	0	160
UNICEF	30	146	176	1913	1913	3826	3	0.83	0.92	250.51	1	160
UNITAID	9	2	11	14	14	28	1	1.00	1.00	0.28	1	187
US Foundations	1	164	165	164	164	328	3	0.92	0.96	23.90	1	210
World Bank	21	129	150	1134	1134	2268	3	0.71	0.85	32.25	0	176
WB_IBRD	20	153	173	1369	1369	2738	3	0.84	0.93	247.82	0	169
WB_IDA	27	117	144	2596	2596	5192	3	0.64	0.81	163.51	3	160
WHO	29	154	183	2476	2476	4952	3	0.90	0.95	314.53	0	160
Corporate Donations	0	2	2	0	2	2	4	0.48	0.49	0.00	1	211
Debt Repayments	0	2	2	0	173	173	4	0.47	0.48	0.00	3	212
Non-OECD DAC Countries	0	17	17	0	710	710	2	0.52	0.55	0.00	2	213
Other	0	11	11	0	285	285	3	0.52	0.53	0.00	2	214
Other OECD DAC Countries	0	8	8	0	220	220	3	0.51	0.52	0.00	2	215
Private Other	0	14	14	0	941	941	3	0.52	0.54	0.00	1	216
Unallocable	0	4	4	0	4	4	4	0.46	0.49	0.00	1	217
Afghanistan	40	0	40	275	0	275	0	0.00	0.00	0.00	0	134
Albania	34	0	34	190	0	190	0	0.00	0.00	0.00	3	122
Algeria	36	0	36	138	0	138	0	0.00	0.00	0.00	2	3
Angola	39	0	39	279	0	279	0	0.00	0.00	0.00	1	21
Anguilla	3	0	3	3	0	3	0	0.00	0.00	0.00	2	170
Antigua and Barbuda	19	0	19	65	0	65	0	0.00	0.00	0.00	2	87
Argentina	34	0	34	118	0	118	0	0.00	0.00	0.00	2	113
Armenia	36	0	36	218	0	218	0	0.00	0.00	0.00	3	75
Azerbaijan	36	0	36	199	0	199	0	0.00	0.00	0.00	3	74
Bahrain	1	0	1	1	0	1	0	0.00	0.00	0.00	0	190
Bangladesh	39	0	39	271	0	271	0	0.00	0.00	0.00	0	135
Barbados	6	0	6	47	0	47	0	0.00	0.00	0.00	2	107

Belarus	30	0	30	119	0	119	0	0.00	0.00	0.00	2	144
Belize	33	0	33	119	0	119	0	0.00	0.00	0.00	2	94
Benin	39	0	39	273	0	273	0	0.00	0.00	0.00	1	43
Bhutan	34	0	34	163	0	163	0	0.00	0.00	0.00	3	70
Bolivia	38	0	38	180	0	180	0	0.00	0.00	0.00	2	108
Bosnia and Herzegovina	35	0	35	182	0	182	0	0.00	0.00	0.00	3	121
Botswana	39	0	39	210	0	210	0	0.00	0.00	0.00	0	18
Brazil	37	0	37	131	0	131	0	0.00	0.00	0.00	2	117
Bulgaria	5	0	5	34	0	34	0	0.00	0.00	0.00	2	156
Burkina Faso	39	0	39	280	0	280	0	0.00	0.00	0.00	1	50
Burundi	39	0	39	264	0	264	0	0.00	0.00	0.00	1	19
Cambodia	37	0	37	266	0	266	0	0.00	0.00	0.00	0	130
Cameroon	39	0	39	277	0	277	0	0.00	0.00	0.00	1	37
Cape Verde	24	0	24	117	0	117	0	0.00	0.00	0.00	3	12
Central African Republic	39	0	39	259	0	259	0	0.00	0.00	0.00	1	14
Chad	39	0	39	266	0	266	0	0.00	0.00	0.00	1	29
Chile	34	0	34	112	0	112	0	0.00	0.00	0.00	2	102
Christmas Island	1	0	1	1	0	1	0	0.00	0.00	0.00	1	209
Colombia	36	0	36	126	0	126	0	0.00	0.00	0.00	2	118
Comoros	39	0	39	223	0	223	0	0.00	0.00	0.00	3	5
Congo	39	0	39	249	0	249	0	0.00	0.00	0.00	1	7
Cook Islands	9	0	9	49	0	49	0	0.00	0.00	0.00	2	149
Costa Rica	35	0	35	131	0	131	0	0.00	0.00	0.00	2	97
Cote d'Ivoire	39	0	39	276	0	276	0	0.00	0.00	0.00	1	20
Croatia	22	0	22	61	0	61	0	0.00	0.00	0.00	2	153
Cuba	36	0	36	166	0	166	0	0.00	0.00	0.00	2	92
Czech Republic	2	0	2	2	0	2	0	0.00	0.00	0.00	1	173
Democratic Republic of the Congo	37	0	37	199	0	199	0	0.00	0.00	0.00	1	46
Djibouti	39	0	39	247	0	247	0	0.00	0.00	0.00	1	25
Dominica	26	0	26	83	0	83	0	0.00	0.00	0.00	2	89
Dominican Republic	37	0	37	159	0	159	0	0.00	0.00	0.00	2	112
Ecuador	37	0	37	128	0	128	0	0.00	0.00	0.00	2	106
Egypt	39	0	39	254	0	254	0	0.00	0.00	0.00	1	35
El Salvador	37	0	37	161	0	161	0	0.00	0.00	0.00	2	100
Equatorial Guinea	38	0	38	197	0	197	0	0.00	0.00	0.00	3	51
Eritrea	39	0	39	255	0	255	0	0.00	0.00	0.00	1	16
Estonia	5	0	5	31	0	31	0	0.00	0.00	0.00	2	154
Ethiopia	39	0	39	288	0	288	0	0.00	0.00	0.00	1	41
Federated States of Micronesia	24	0	24	64	0	64	0	0.00	0.00	0.00	2	64
Fiji	26	0	26	81	0	81	0	0.00	0.00	0.00	2	139
Gabon	38	0	38	210	0	210	0	0.00	0.00	0.00	0	47
Georgia	36	0	36	245	0	245	0	0.00	0.00	0.00	3	81
Ghana	39	0	39	284	0	284	0	0.00	0.00	0.00	1	40
Global	43	0	43	260	0	260	0	0.00	0.00	0.00	1	6

Grenada	30	0	30	85	0	85	0	0.00	0.00	0.00	2	90
Guatemala	37	0	37	170	0	170	0	0.00	0.00	0.00	2	115
Guinea	39	0	39	270	0	270	0	0.00	0.00	0.00	1	31
Guinea-Bissau	39	0	39	259	0	259	0	0.00	0.00	0.00	1	30
Guyana	34	0	34	156	0	156	0	0.00	0.00	0.00	2	98
Haiti	38	0	38	234	0	234	0	0.00	0.00	0.00	2	111
Honduras	38	0	38	186	0	186	0	0.00	0.00	0.00	2	109
Hungary	3	0	3	3	0	3	0	0.00	0.00	0.00	1	166
India	39	0	39	274	0	274	0	0.00	0.00	0.00	0	136
Indonesia	39	0	39	265	0	265	0	0.00	0.00	0.00	0	132
Iran	36	0	36	142	0	142	0	0.00	0.00	0.00	2	73
Iraq	37	0	37	195	0	195	0	0.00	0.00	0.00	0	76
Jamaica	36	0	36	143	0	143	0	0.00	0.00	0.00	2	103
Jordan	37	0	37	198	0	198	0	0.00	0.00	0.00	0	80
Kazakhstan	37	0	37	212	0	212	0	0.00	0.00	0.00	3	78
Kenya	39	0	39	285	0	285	0	0.00	0.00	0.00	1	48
Kiribati	28	0	28	98	0	98	0	0.00	0.00	0.00	2	58
Kosovo	32	0	32	142	0	142	0	0.00	0.00	0.00	3	143
Kyrgyzstan	36	0	36	225	0	225	0	0.00	0.00	0.00	3	77
Laos	37	0	37	258	0	258	0	0.00	0.00	0.00	0	127
Latvia	5	0	5	7	0	7	0	0.00	0.00	0.00	1	157
Lebanon	38	0	38	162	0	162	0	0.00	0.00	0.00	0	68
Lesotho	39	0	39	253	0	253	0	0.00	0.00	0.00	1	22
Liberia	39	0	39	269	0	269	0	0.00	0.00	0.00	1	33
Libya	33	0	33	123	0	123	0	0.00	0.00	0.00	0	2
Lithuania	5	0	5	7	0	7	0	0.00	0.00	0.00	1	158
Macedonia	30	0	30	131	0	131	0	0.00	0.00	0.00	2	145
Madagascar	39	0	39	276	0	276	0	0.00	0.00	0.00	1	38
Malawi	39	0	39	277	0	277	0	0.00	0.00	0.00	1	44
Malaysia	31	0	31	132	0	132	0	0.00	0.00	0.00	0	140
Maldives	32	0	32	110	0	110	0	0.00	0.00	0.00	3	66
Mali	40	0	40	282	0	282	0	0.00	0.00	0.00	1	45
Malta	1	0	1	1	0	1	0	0.00	0.00	0.00	0	180
Marshall Islands	21	0	21	76	0	76	0	0.00	0.00	0.00	0	138
Mauritania	39	0	39	259	0	259	0	0.00	0.00	0.00	1	34
Mauritius	33	0	33	112	0	112	0	0.00	0.00	0.00	2	0
Mayotte	1	0	1	1	0	1	0	0.00	0.00	0.00	0	191
Mexico	37	0	37	161	0	161	0	0.00	0.00	0.00	2	114
Moldova	33	0	33	185	0	185	0	0.00	0.00	0.00	3	125
Mongolia	37	0	37	213	0	213	0	0.00	0.00	0.00	0	124
Montenegro	31	0	31	137	0	137	0	0.00	0.00	0.00	3	142
Montserrat	25	0	25	72	0	72	0	0.00	0.00	0.00	2	91
Morocco	39	0	39	218	0	218	0	0.00	0.00	0.00	1	55
Mozambique	39	0	39	288	0	288	0	0.00	0.00	0.00	1	36

Myanmar	37	0	37	258	0	258	0	0.00	0.00	0.00	0	131
Namibia	39	0	39	222	0	222	0	0.00	0.00	0.00	1	17
Nauru	19	0	19	52	0	52	0	0.00	0.00	0.00	2	59
Nepal	39	0	39	265	0	265	0	0.00	0.00	0.00	0	86
Netherlands Antilles	2	0	2	12	0	12	0	0.00	0.00	0.00	0	177
Nicaragua	37	0	37	201	0	201	0	0.00	0.00	0.00	2	110
Niger	39	0	39	276	0	276	0	0.00	0.00	0.00	1	42
Nigeria	39	0	39	287	0	287	0	0.00	0.00	0.00	1	52
Niue	18	0	18	64	0	64	0	0.00	0.00	0.00	2	63
North Korea	32	0	32	127	0	127	0	0.00	0.00	0.00	2	72
Northern Mariana Islands	2	0	2	2	0	2	0	0.00	0.00	0.00	2	197
Oman	5	0	5	5	0	5	0	0.00	0.00	0.00	1	164
Pakistan	39	0	39	273	0	273	0	0.00	0.00	0.00	0	137
Palau	18	0	18	50	0	50	0	0.00	0.00	0.00	2	62
Palestine	34	0	34	125	0	125	0	0.00	0.00	0.00	2	151
Panama	35	0	35	142	0	142	0	0.00	0.00	0.00	2	105
Papua New Guinea	32	0	32	138	0	138	0	0.00	0.00	0.00	0	128
Paraguay	36	0	36	116	0	116	0	0.00	0.00	0.00	2	95
Peru	37	0	37	131	0	131	0	0.00	0.00	0.00	2	104
Philippines	39	0	39	248	0	248	0	0.00	0.00	0.00	0	120
Poland	4	0	4	6	0	6	0	0.00	0.00	0.00	1	168
Romania	5	0	5	34	0	34	0	0.00	0.00	0.00	2	155
Russia	8	0	8	36	0	36	0	0.00	0.00	0.00	2	147
Rwanda	39	0	39	276	0	276	0	0.00	0.00	0.00	1	27
Saint Helena	33	0	33	130	0	130	0	0.00	0.00	0.00	0	10
Saint Kitts and Nevis	8	0	8	47	0	47	0	0.00	0.00	0.00	2	152
Saint Lucia	33	0	33	107	0	107	0	0.00	0.00	0.00	2	93
Saint Vincent and the Grenadines	32	0	32	95	0	95	0	0.00	0.00	0.00	2	88
Samoa	26	0	26	106	0	106	0	0.00	0.00	0.00	3	65
Sao Tome and Principe	38	0	38	230	0	230	0	0.00	0.00	0.00	3	4
Saudi Arabia	5	0	5	5	0	5	0	0.00	0.00	0.00	1	172
Senegal	39	0	39	283	0	283	0	0.00	0.00	0.00	1	39
Serbia	35	0	35	167	0	167	0	0.00	0.00	0.00	2	146
Seychelles	33	0	33	97	0	97	0	0.00	0.00	0.00	2	1
Sierra Leone	39	0	39	270	0	270	0	0.00	0.00	0.00	1	49
Slovakia	2	0	2	2	0	2	0	0.00	0.00	0.00	1	165
Slovenia	8	0	8	8	0	8	0	0.00	0.00	0.00	0	159
Solomon Islands	26	0	26	128	0	128	0	0.00	0.00	0.00	3	82
Somalia	39	0	39	252	0	252	0	0.00	0.00	0.00	1	15
South Africa	39	0	39	260	0	260	0	0.00	0.00	0.00	0	24
South Korea	7	0	7	7	0	7	0	0.00	0.00	0.00	0	167
South Sudan	39	0	39	245	0	245	0	0.00	0.00	0.00	1	13
Sri Lanka	37	0	37	231	0	231	0	0.00	0.00	0.00	0	126
Sudan	39	0	39	272	0	272	0	0.00	0.00	0.00	1	26

Suriname	34	0	34	107	0	107	0	0.00	0.00	0.00	2	96
Swaziland	38	0	38	201	0	201	0	0.00	0.00	0.00	0	11
Syria	38	0	38	195	0	195	0	0.00	0.00	0.00	0	67
Tajikistan	37	0	37	248	0	248	0	0.00	0.00	0.00	0	83
Tanzania	39	0	39	285	0	285	0	0.00	0.00	0.00	1	53
Thailand	38	0	38	193	0	193	0	0.00	0.00	0.00	0	85
The Gambia	39	0	39	248	0	248	0	0.00	0.00	0.00	1	28
Timor-Leste	37	0	37	231	0	231	0	0.00	0.00	0.00	0	79
Togo	39	0	39	255	0	255	0	0.00	0.00	0.00	1	9
Tokelau	13	0	13	18	0	18	0	0.00	0.00	0.00	2	148
Tonga	23	0	23	99	0	99	0	0.00	0.00	0.00	3	60
Trinidad and Tobago	11	0	11	52	0	52	0	0.00	0.00	0.00	2	116
Tunisia	37	0	37	172	0	172	0	0.00	0.00	0.00	2	8
Turkey	29	0	29	142	0	142	0	0.00	0.00	0.00	0	141
Turkmenistan	36	0	36	158	0	158	0	0.00	0.00	0.00	3	69
Turks and Caicos Islands	2	0	2	2	0	2	0	0.00	0.00	0.00	2	182
Tuvalu	21	0	21	93	0	93	0	0.00	0.00	0.00	3	61
Uganda	39	0	39	286	0	286	0	0.00	0.00	0.00	1	54
Ukraine	32	0	32	181	0	181	0	0.00	0.00	0.00	0	123
Unallocated/Unspecified	45	0	45	357	0	357	0	0.00	0.00	0.00	1	56
Uruguay	31	0	31	78	0	78	0	0.00	0.00	0.00	2	101
Uzbekistan	35	0	35	253	0	253	0	0.00	0.00	0.00	0	129
Vanuatu	25	0	25	76	0	76	0	0.00	0.00	0.00	2	71
Venezuela	34	0	34	106	0	106	0	0.00	0.00	0.00	2	99
Vietnam	39	0	39	270	0	270	0	0.00	0.00	0.00	0	133
Wallis and Futuna Islands	18	0	18	27	0	27	0	0.00	0.00	0.00	0	150
Yemen	37	0	37	249	0	249	0	0.00	0.00	0.00	3	84
Zambia	39	0	39	283	0	283	0	0.00	0.00	0.00	1	32
Zimbabwe	39	0	39	275	0	275	0	0.00	0.00	0.00	1	23

Twitter network analysis statistics report

Label	indegree	outdegree	Degree	weighted indegree	weighted outdegree	Weighted Degree	Eccentricity	closnesscentrality	harmonicclosnesscentrality	betweenesscentrality	modularity_class	strongcompnum
United States	0	8	8	0	30	30	3	0.38	0.44	0.00	0	67
United Kingdom	0	8	8	0	29	29	3	0.38	0.44	0.00	1	68
BMGF	0	8	8	0	35	35	3	0.38	0.44	0.00	0	69
WHO	3	9	12	17	29	46	2	0.54	0.58	23.50	0	66
World Bank	3	8	11	16	31	47	2	0.54	0.58	19.65	1	65
UNAIDS	3	9	12	8	18	26	2	0.54	0.58	23.50	0	64

UNFPA	3	8	11	10	20	30	2	0.54	0.58	19.65	1	63
UNICEF	3	9	12	13	28	41	2	0.54	0.58	23.50	1	62
UNITAID	3	8	11	7	21	28	2	0.54	0.58	20.21	4	61
GAVI	3	9	12	9	24	33	2	0.54	0.58	23.50	4	60
GFATM	3	9	12	14	30	44	2	0.54	0.58	23.50	3	59
Oxfam	8	10	18	28	10	38	1	1.00	1.00	40.64	1	58
CDC	8	10	18	19	10	29	1	1.00	1.00	72.46	2	56
EU CDC	6	10	16	13	10	23	1	1.00	1.00	62.06	3	51
NIH	8	10	18	13	10	23	1	1.00	1.00	87.07	4	43
FAO	7	9	16	13	9	22	1	1.00	1.00	67.06	1	35
UNDP	8	10	18	33	10	43	1	1.00	1.00	41.00	1	28
MSF	8	10	18	32	10	42	1	1.00	1.00	56.78	3	23
PATH	8	10	18	30	10	40	1	1.00	1.00	59.94	4	17
Save the Children	8	9	17	20	9	29	1	1.00	1.00	46.99	1	9
Access	1	0	1	1	0	1	0	0.00	0.00	0.00	4	16
Africa	7	0	7	7	0	7	0	0.00	0.00	0.00	1	8
Agriculture	1	0	1	1	0	1	0	0.00	0.00	0.00	1	34
Biodiversity	1	0	1	1	0	1	0	0.00	0.00	0.00	1	33
Breastfeeding	1	0	1	1	0	1	0	0.00	0.00	0.00	4	15
Cancer	2	0	2	2	0	2	0	0.00	0.00	0.00	4	14
Child Marriage	0	0	0	0	0	0	0	0.00	0.00	0.00	5	70
Children	5	0	5	5	0	5	0	0.00	0.00	0.00	1	7
Cholera	1	0	1	1	0	1	0	0.00	0.00	0.00	3	22
Climate Change	3	0	3	3	0	3	0	0.00	0.00	0.00	1	27
Development	0	0	0	0	0	0	0	0.00	0.00	0.00	6	71
Diarrhea	1	0	1	1	0	1	0	0.00	0.00	0.00	2	55
Discrimination	0	0	0	0	0	0	0	0.00	0.00	0.00	7	72
Donations	1	0	1	1	0	1	0	0.00	0.00	0.00	1	6
E. Coli	1	0	1	1	0	1	0	0.00	0.00	0.00	2	54
Ebola	4	0	4	4	0	4	0	0.00	0.00	0.00	3	13
Education	2	0	2	2	0	2	0	0.00	0.00	0.00	1	5
FGM	1	0	1	1	0	1	0	0.00	0.00	0.00	1	26
Families	1	0	1	1	0	1	0	0.00	0.00	0.00	1	32
Family Planning	0	0	0	0	0	0	0	0.00	0.00	0.00	8	73
Farmers	1	0	1	1	0	1	0	0.00	0.00	0.00	1	31
Fisheries	1	0	1	1	0	1	0	0.00	0.00	0.00	1	30
Food Security	4	0	4	4	0	4	0	0.00	0.00	0.00	1	4
Forests	1	0	1	1	0	1	0	0.00	0.00	0.00	1	29
Funding	1	0	1	1	0	1	0	0.00	0.00	0.00	4	42
HIV/AIDS	4	0	4	4	0	4	0	0.00	0.00	0.00	1	21
Heart Disease	1	0	1	1	0	1	0	0.00	0.00	0.00	4	41
Hepatitis	1	0	1	1	0	1	0	0.00	0.00	0.00	3	50
Human Rights	0	0	0	0	0	0	0	0.00	0.00	0.00	9	74

Humanitarian Aid	3	0	3	3	0	3	0	0.00	0.00	0.00	3	3
Influenza	2	0	2	2	0	2	0	0.00	0.00	0.00	2	49
Innovation	1	0	1	1	0	1	0	0.00	0.00	0.00	4	12
Malaria	3	0	3	3	0	3	0	0.00	0.00	0.00	1	11
Measles	2	0	2	2	0	2	0	0.00	0.00	0.00	3	48
Mothers	0	0	0	0	0	0	0	0.00	0.00	0.00	10	75
News	1	0	1	1	0	1	0	0.00	0.00	0.00	4	40
Nutrition	0	0	0	0	0	0	0	0.00	0.00	0.00	11	76
Online	0	0	0	0	0	0	0	0.00	0.00	0.00	12	77
Outbreaks	1	0	1	1	0	1	0	0.00	0.00	0.00	3	47
Pneumonia	1	0	1	1	0	1	0	0.00	0.00	0.00	1	57
Pneuomonia	2	0	2	2	0	2	0	0.00	0.00	0.00	1	2
Polio	0	0	0	0	0	0	0	0.00	0.00	0.00	13	78
Poverty	0	0	0	0	0	0	0	0.00	0.00	0.00	14	79
Prevention	1	0	1	1	0	1	0	0.00	0.00	0.00	2	53
Rare Disease	1	0	1	1	0	1	0	0.00	0.00	0.00	4	39
Refugees	3	0	3	3	0	3	0	0.00	0.00	0.00	3	1
Report	1	0	1	1	0	1	0	0.00	0.00	0.00	3	46
Research	1	0	1	1	0	1	0	0.00	0.00	0.00	4	38
Sanitation	0	0	0	0	0	0	0	0.00	0.00	0.00	15	80
Schools	1	0	1	1	0	1	0	0.00	0.00	0.00	1	0
South America	0	0	0	0	0	0	0	0.00	0.00	0.00	16	81
Stress	1	0	1	1	0	1	0	0.00	0.00	0.00	4	37
Surveillance	1	0	1	1	0	1	0	0.00	0.00	0.00	3	45
Testing	0	0	0	0	0	0	0	0.00	0.00	0.00	17	82
Treatment	1	0	1	1	0	1	0	0.00	0.00	0.00	3	20
Tubercolosis	2	0	2	2	0	2	0	0.00	0.00	0.00	3	19
Vaccines	2	0	2	2	0	2	0	0.00	0.00	0.00	2	10
Veterans	1	0	1	1	0	1	0	0.00	0.00	0.00	4	36
Violence	1	0	1	1	0	1	0	0.00	0.00	0.00	3	18
Water	3	0	3	3	0	3	0	0.00	0.00	0.00	2	25
West Nile	1	0	1	1	0	1	0	0.00	0.00	0.00	3	44
Women	3	0	3	3	0	3	0	0.00	0.00	0.00	2	24
Zika	1	0	1	1	0	1	0	0.00	0.00	0.00	2	52