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Characterizing the Reaction of Doctors to COVID-19 on Twitter

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Abstract

With the recent surges of new COVID-19 variants, clear public health messaging on social media has become more vital than ever. One important source of public health information are messages and reactions expressed by medical professionals. However, the content of messages promulgated by these experts are not fully understood. In this study, we demonstrate how unique Twitter data can be used to explore doctors' reactions to the early months of the COVID-19 pandemic. We examine 265,412 English-language tweets about COVID-19 from doctors and a comparable subset of tweets from non-doctors using two-sample t-tests with a Bonferroni-corrected significance threshold. We elucidate how discussion differed over time and in comparison to non-doctors. Tweets spiked surrounding major events and in locations with rising case numbers. Discussion from doctors initially focused on the origin of the virus in Wuhan, later switching to calls to "stay home." Doctors tweeted more often about public health and healthcare workers, whereas non-doctors were more likely to tweet about political topics, including China and the Trump administration. The differences in how doctors and non-doctors engage about COVID-19 can provide insight into the similarities and differences in communication between medical experts and the public. For example, in future surges, experts could tailor their health messaging around topics of interest to the general public to increase engagement. Alternatively, topics that differ across groups may warrant educational messages to better align expert and public perspectives. By identifying both areas of shared purpose and differences in prioritized topics, future public health communications may benefit from analyses that compare the social media messages promulgated by various groups.

Keywords

COVID-19; social media; Twitter; doctors

Introduction

Social media platforms can allow researchers to examine public health perceptions and messaging by various groups. In particular, understanding differences between experts and

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the general public may help identify the types of messaging conducted by experts, the set of issues salient to each group, and potential gaps in knowledge between groups. Doctors constitute one important source of public health information. However, the content of messages promulgated by these experts are not fully understood. This paper leverages unique data from Twitter to examine the discussion around COVID-19 on social media during the initial phase of the pandemic. We use data from Twitter to retrospectively explore doctors' reactions to the COVID-19 pandemic by elucidating how discussion differed across time and in comparison to non-doctors.

Contrasting doctors and non-doctors can provide evidence on whether certain ideas, narratives, or public health measures are of interest to multiple groups or remain the focus of particular subpopulations. Doctors, defined as medical professionals who have earned an M.D. or D.O., are potentially knowledgeable consumers and producers of public health information. We hypothesize that the messaging of doctors differs from the general population in topics of discussion, and that these differences reflect a greater focus on public health and medical issues. Topics that differ significantly between doctors and non-doctors could be potential targets for future messaging campaigns.

The study most closely related to ours examined tweets from a manually selected sample of 119 doctors and found that these physicians tweeted about misinformation, scientific findings, and concerns about health systems and workers (Wahbeh et al., 2020). Our study augments this prior work by leveraging a larger dataset of the near universe of 43,877 self-identified doctors on Twitter and by employing a comparison sample of tweets by non-doctors to better identify the topics of conversation that were uniquely promoted by doctors.

Other related studies have analyzed large samples of tweets from the general public by characterizing discussion topics (Abd-Alrazaq et al., 2020) and applying sentiment analysis algorithms to quantify the share of tweets expressing fear, anger, joy, or sadness over time (Lwin et al., 2020). Our study also extracts discussion topics from a large sample of tweets but differs from these prior papers by characterizing differences between two important subgroups: doctors and non-doctors. Noar and Austin (2020) focus on a subgroup (public officials), but qualitatively reflect on specific quotes and do not perform quantitative analyses. They report that certain messages such as “stay home” dominated this period, an observation that we confirm in our empirical analysis.

Our paper augments this existing literature by examining communication from a specific subgroup, doctors, using a larger dataset than prior work. More broadly, we demonstrate how methods employed to analyze large samples can be used to draw distinctions between groups and facilitate better targeting of health communication in the future.

Background

With the report of the first case of COVID-19 in Washington State in late January, increased media coverage raised awareness and interest among the U.S. population.² The U.S. media covered its origin in Wuhan, China,³ the death of whistleblower Dr. Li Wenliang,⁴ the outbreak on the Diamond Princess cruise,⁵ and implementation of social distancing

measures.⁶ Doctors took a vocal role in the pandemic, writing numerous articles, opinion pieces, and social media posts focused on obtaining adequate personal protective equipment (PPE)⁷ and sharing their opinions regarding the pandemic response.

Twitter, a social media network, offers another window into how the COVID-19 pandemic was experienced and described by over 60 million active users in the U.S.⁸ With 71% of Americans receiving news and information from social media,⁹ data on the content shared on social media platforms such as Twitter may offer insight into the beliefs and opinions of various subpopulations.

Methods

Data Collection

Tweets about COVID-19 were identified using the COVID-19-TweetIDS dataset originally prepared by Chen, Lerman, and Ferrera encompassing all 102,904,046 tweets from 01/22/2020 to 04/30/2020 that include “coronavirus,” “COVID-19,” and other related terms (Chen et al., 2020). This corpus of tweets related to COVID-19 was compiled in real time using a continuously updating list of terms and accounts tracking COVID-19. We acknowledge that using certain keywords and accounts is an imperfect method of capturing all tweets related to COVID-19. However, this method provides a nearly comprehensive corpus within the technical limitations set by the Twitter API.

Data Processing

We first limited our sample to English-language tweets ($n = 68,108,441$). We extracted the subset of tweets created by doctors by identifying Twitter users whose user descriptions contained the words “doctor,” “physician,” “MD,” “DO,” “Dr,” and variants thereof. To compare doctors’ tweets to those of the general population, we drew a random sample of 268,301 English-language tweets from the full dataset, excluding any tweets by doctors.¹⁰ We excluded tweets made on 02/23/2020 and 03/02/2020 due to lack of data collection during these dates.

²Rabin, R. C. (2020). First Patient With the Mysterious Illness Is Identified in the U.S. *New York Times*, 10. <https://www.nytimes.com/2020/01/21/health/cdc-coronavirus.html>

³Qin, A., & Hernández, J. C. (2020). China Reports First Death From New Virus. *The New York Times*. <https://www.nytimes.com/2020/01/10/world/asia/china-virus-wuhan-death.html>

⁴Buckley, C. (2020). Chinese Doctor, Silenced After Warning of Outbreak, Dies From Coronavirus. *The New York Times*, 1. <https://www.nytimes.com/2020/02/06/world/asia/chinese-doctor-Li-Wenliang-coronavirus.html>

⁵Yamamitsu, E., & Dooley, B. (2020). Trapped on a Cruise Ship by the Coronavirus: When Is Breakfast? *The New York Times*. <https://www.nytimes.com/2020/02/05/world/asia/japan-coronavirus-cruise-ship.html>

⁶Kaiser Family Foundation. (2020). *State Data and Policy Actions to Address Coronavirus*. <https://www.kff.org/coronavirus-covid-19/issue-brief/state-data-and-policy-actions-to-address-coronavirus/>

⁷Padilla, M. (2020). ‘It Feels Like a War Zone’: Doctors and Nurses Plead for Masks on Social Media. *The New York Times*. <https://www.nytimes.com/2020/03/19/us/hospitals-coronavirus-ppe-shortage.html>

⁸Number of monetizable daily active Twitter users (mDAU) worldwide from 1st quarter 2017 to 3rd quarter 2021. <https://www.statista.com/statistics/970920/monetizable-daily-active-twitter-users-worldwide/>

⁹US Social Network Users: eMarketer’s Estimates for 2018–2022. <https://www.emarketer.com/Report/US-Social-Network-Users-eMarketers-Estimates-20182022/2002222>

¹⁰We elected to use a random sample of all non-doctor tweets rather than a matched sample of non-doctor tweets matched on characteristics such as follower count. We did this to avoid introducing potential biases stemming from the choice of matching variable(s) and to compare doctors to the non-doctor population as a whole. This reveals aggregate differences between the two groups, for example that doctors are more likely to include a location in their user description and slightly more likely to post original tweets rather than retweets (Table 1). Using a matched sample would implement a different, though also potentially interesting comparison between doctors and the subset of non-doctors with similar characteristics.

Data Analysis

To identify the most prominent topics of discussion by doctors and non-doctors, we extracted the set of all words and word pairings contained in each sample using the Bigram Frequencies function from the Natural Language Toolkit (Bird et al., 2009), which extracts the most common word pairings from a given text input and reports the number of times each word pairing appears. We excluded filler words like “a,” “the,” “this,” or “is” as well as alternate spellings of COVID-19 and “rt,” an abbreviation of retweet. We computed the proportion of tweets containing each word pairing and compared these proportions between doctors and non-doctors, excluding word pairings that appear in fewer than 10 tweets in either population. We used two-sample t-tests to assess whether particular word pairings were more commonly used by doctors or non-doctors and employed a Bonferroni-corrected significance threshold to ensure a family-wise error rate = 0.05.

We applied the Python library GeoPandas (Jordahl, 2014), which extracts a location from a text input by matching it to a list of established locations, to user location text fields to establish the geographic locations of doctors at the city level. We then computed the proportion of daily tweets with an identifiable location that were associated with each city. This allowed us to examine how the geographic distribution of COVID-19-related Twitter activity evolved over time for the U.S. cities with the highest number of tweets by doctors.

Data collection, processing, and analyses were conducted in Python (McKinney, 2010) using the Pandas package (The pandas development team, 2020). Additional analyses were conducted in STATA Version 16 (StataCorp, 2019). Data were stored on a SQLITE database (Hipp, 2020).

Results

There were 265,412 English-language tweets about COVID-19 by self-identified doctors from 01/22/2020 to 04/30/2020 (Table 1). There were 43,877 distinct Twitter users whose user descriptions contained language that identified them as doctors. We were able to associate a location with 80% of doctors and 83% of tweets by doctors, compared to 67% of non-doctors and 67% of non-doctor tweets.

Of the users we identified as doctors, 15,348 (35%) provided links to personal websites and 490 (1.1%) were verified accounts. Common words found in user descriptions of self-identified doctors included “doctor,” “md,” “medical,” and “health.” The most common pairing of words was “medical doctor.” The average number of followers was 1,720 and the average number of accounts followed was 876. Self-identified doctors tweeted about COVID-19 an average of 6.0 times over our time period; the distribution of the number of COVID-19-related tweets was very skewed, with most doctors tweeting fewer than 5 times.

Doctors most frequently tweeted about COVID-19 at the end of January (01/29/2020 – 01/31/2020) and beginning of March (02/28/2020 – 03/04/2020), with a doubling and tripling in the number of tweets respectively (Figure 1). This pattern was similar for non-doctors. The first spike coincides with the designation of COVID-19 as a global pandemic by the World Health Organization on 01/30/2020 as well as an increase in tweets mentioning

“China.” The drivers of the second spike (02/28/2020 – 03/04/2020) were more numerous and included reactions to President Trump (in particular, his reference to COVID-19 as a “hoax” at a campaign rally), a viral tweet explaining the importance of hand washing, the first U.S. death due to COVID-19 (reported on 02/29/2020), and increasing discussion about COVID-19 case numbers and China.

The top 10 most common words used in tweets during this time period were “coronavirus,” “China,” “COVID-19,” “lockdown,” “pandemic,” “cases,” “new,” “health,” “Wuhan,” and “outbreak.” Topics of discussion initially focused on the new public health emergency - the novel coronavirus outbreak in Wuhan. In February, certain news stories rose into the top 5 ranking, including whistleblower Dr. Li Wenliang, the outbreak aboard the Diamond Princess cruise ship, and Mike Pence being chosen to lead the coronavirus task force. In March, the topics of staying home and social distancing took the forefront, retaining the top two ranks through the end of April.

The geographic distribution of doctor tweets evolved over time. New York, which experienced a large rise in COVID-19 cases and deaths in March and April, demonstrates a large and persistent increase in the share of tweets. Doctors throughout the U.S. tweeted about COVID-19, with the largest number of tweets originating primarily from New York, followed by Washington D.C., Los Angeles, Houston, Boston, and Chicago. Non-doctors in the U.S. tweeted from an almost identical set of top six cities, with Seattle taking the place of Boston.

Figure 2 plots the share of each day’s tweets involving a specific pair of words, to better illustrate the transition in discussion topics. The share of tweets including “Wuhan China” or “novel coronavirus” is initially high in late January, together consisting of about 10% of all COVID-19-related tweets. This share decreases significantly by late February and early March. The specific term “novel coronavirus” was used more frequently by doctors than non-doctors (appearing in 1.6% vs. 0.9% of all tweets, $P = 0.0012$). In mid-March, there is an increase in the share of tweets including the terms “social distancing” or “stay home,” reflecting the widespread introduction of non-pharmaceutical interventions to stem viral transmission.¹¹ The overall trajectory of the selected terms over time was similar between both doctors and non-doctors, reflecting a common awareness of the importance of public health behaviors.

Although time series patterns were qualitatively similar between doctors and non-doctors, we found differences in the prevalence of specific terms. Figure 3a compares the prevalence of word pairings between doctors and non-doctors, excluding synonyms for COVID-19. Overall, there is a high correlation between both populations ($r = 0.90$, $P \approx 0$). For example, the terms “stay home” and “social distancing” are highly prevalent for both populations. However, certain health-related terms are more common among doctors. These include “public health,” “health care,” and “healthcare workers.” Terms that were relatively more common among non-doctor tweets clustered around politics (e.g. “President Trump” and

¹¹Terms about social distancing and stay home were initially tracked starting on 3/13/2020 and 3/16/2020-3/19/2020. Because this partially coincides with the sharp increases in Figure 2, it is possible that the rise in these terms began earlier.

“White House”) and specific locations or ethnicities (e.g. “Hong Kong,” “Wuhan China,” and “Chinese people”).

The prevalence distribution is right-skewed such that a handful of words have exceedingly high prevalence. To address this, Figure 3b provides a closer look at word pairings with lower prevalences that may help differentiate tweets between doctors and non-doctors. Consistent with Figure 3a, we find that doctors are more likely to use the terms “health workers” and “infectious disease.” Doctors also appear to discuss different news sources, including National Public Radio and the World Health Organization; non-doctors’ tweets more frequently contain the term “breaking news.” The term “fake news” is prevalent among both groups. Doctors tweeted more about certain issues: the terms “stop buying,” “buying masks,” and “n95 masks” reflect the early shortage of PPE affecting healthcare workers during the early months of the pandemic. In contrast, non-doctors’ tweets more commonly included political terms such as “communist party” and “communist China.”

Figure 4 assesses the statistical significance of a collection of 78 terms from Figure 3a and 3b. This further highlights terms that may not be highly prevalent in either group but are highly specific to one group in particular. The results of these statistical tests are broadly consistent with the observations in Figure 3. Doctors tweeted more frequently about “healthcare workers” and “public health,” whereas non-doctors tweeted more frequently about “Hong Kong” and “President Trump.” Of note, both doctors and non-doctors frequently tweeted about general protective behaviors, with terms including “stay home,” “social distancing,” and “wear mask.”

Discussion

Our analysis shows both strong commonalities as well as significant differences in the topics discussed by doctors and non-doctors on Twitter. Self-identified doctors tended to address topics related to COVID-19 from the medical perspective, with more frequent references to public health, the World Health Organization, PPE shortages, hand washing, and healthcare workers. In comparison, discussion regarding politics or ethnic groupings were more common amongst non-physicians. Surprisingly, both groups tweeted equally heavily about general protective behaviors like social distancing and staying home.

Our findings are consistent with a model where doctors responded to the COVID-19 pandemic by both promoting public health behaviors (i.e., social distancing) as well as acting as advocates for their own profession, reflected in phrases such as “health workers” and “stop buying [masks].” They were also more likely to use technical language (e.g., “public health emergency of international concern”). The data also show that doctors clearly avoided political topics, with far fewer tweets including the terms “President Trump,” “Joe Biden,” or “communist party.” Taken together, these differences support our hypothesis that doctors differed from the general population: doctors avoided overtly political topics and implored the public to “stop buying masks” to maintain supplies of protective equipment for health care workers. Contrary to our original hypothesis, however, both doctors and the general public promoted social distancing behaviors equally and beginning at a similar date. This finding pushes against a narrative that doctors were uniquely focused on promoting

public health messages or that doctors were very early promulgators of these messages. This suggests that Twitter data may be a promising way to measure the differential responses of specific sub-populations to major events.

Our methodology could be applied to improve future public health messaging. For example, researchers could collect data on tweets mentioning vaccination, and follow our methods to identify topics that differ significantly between experts (e.g., doctors) and non-doctors. This could reveal specific narratives contributing to vaccine hesitancy, which would likely be enriched in the non-doctor sample. Groups could also be defined based on political party affiliation, which could reveal group-specific concerns. Public health messaging could be designed to address the most common concerns among all groups or tailored to the narratives of specific subgroups (e.g., Democrats vs. Republicans).

We have made additional observations that support the ability of the Twitter data to accurately reflect the subjects, timing, and geographical distribution of public discourse. First, the most common word pairings reveal distinct subjects of discussion among self-identified doctors that changed over time, shifting from tweets about a novel respiratory illness in China in February to a large share of tweets related to social distancing and staying home from both doctors and non-doctors. The locations of COVID-19-related Twitter activity reflect major cities and areas that were most hard hit by the pandemic. This suggests that Twitter data could be useful to measure place-specific messaging in future studies.

Our study has limitations. The underlying database only identifies tweets that match a list of terms related to COVID-19; this may exclude some relevant tweets. Because we limit to English-language tweets, our study may not generalize well to non-English speaking countries. Although we attempt to capture the universe of doctors on Twitter, we rely on information provided in user descriptions, which may not perfectly identify physicians. We did not directly sample other expert health communicator such as nurses and health organizations; thus, our findings may not generalize to these populations. Moreover, Twitter represents one social media platform among many, and may not be representative of all social media users. In the U.S., Twitter users are more likely to be below 50 years of age and college graduates, but are well-matched to the general population in terms of gender, race, and ethnicity.¹² Despite these limitations, this study provides a foundation for characterizing doctors' reactions to the COVID-19 pandemic.

Conclusion

Twitter data from self-identified doctors on COVID-19 reveals trends about doctors' reactions to events surrounding the pandemic and how doctors differed in discourse from non-doctors. We hypothesized that doctors would predominantly tweet about medical issues and public health. Overall, our analysis supports this hypothesis, as doctors were more likely to tweet from the medical perspective of COVID-19, focusing on PPE, healthcare

¹²Wojcik, S & Hughes, A (2019). *Sizing Up Twitter Users*. Pew Research Center. <https://www.pewresearch.org/internet/2019/04/24/sizing-up-twitter-users/>

workers, and public health. In contrast, non-doctors were more likely to tweet terms related to politics, China, and ethnic distinctions. However, we also found strong commonalities between doctors and non-doctors, with a high correlation in the prevalence of word pairings and emphasis on general protective behaviors. Twitter represents an avenue to understanding the medical community's reaction to COVID-19. More broadly, we demonstrate how Twitter data can be leveraged to compare the social media responses of different groups and inform public health messaging for subsequent waves, vaccination drives, and emerging variants.

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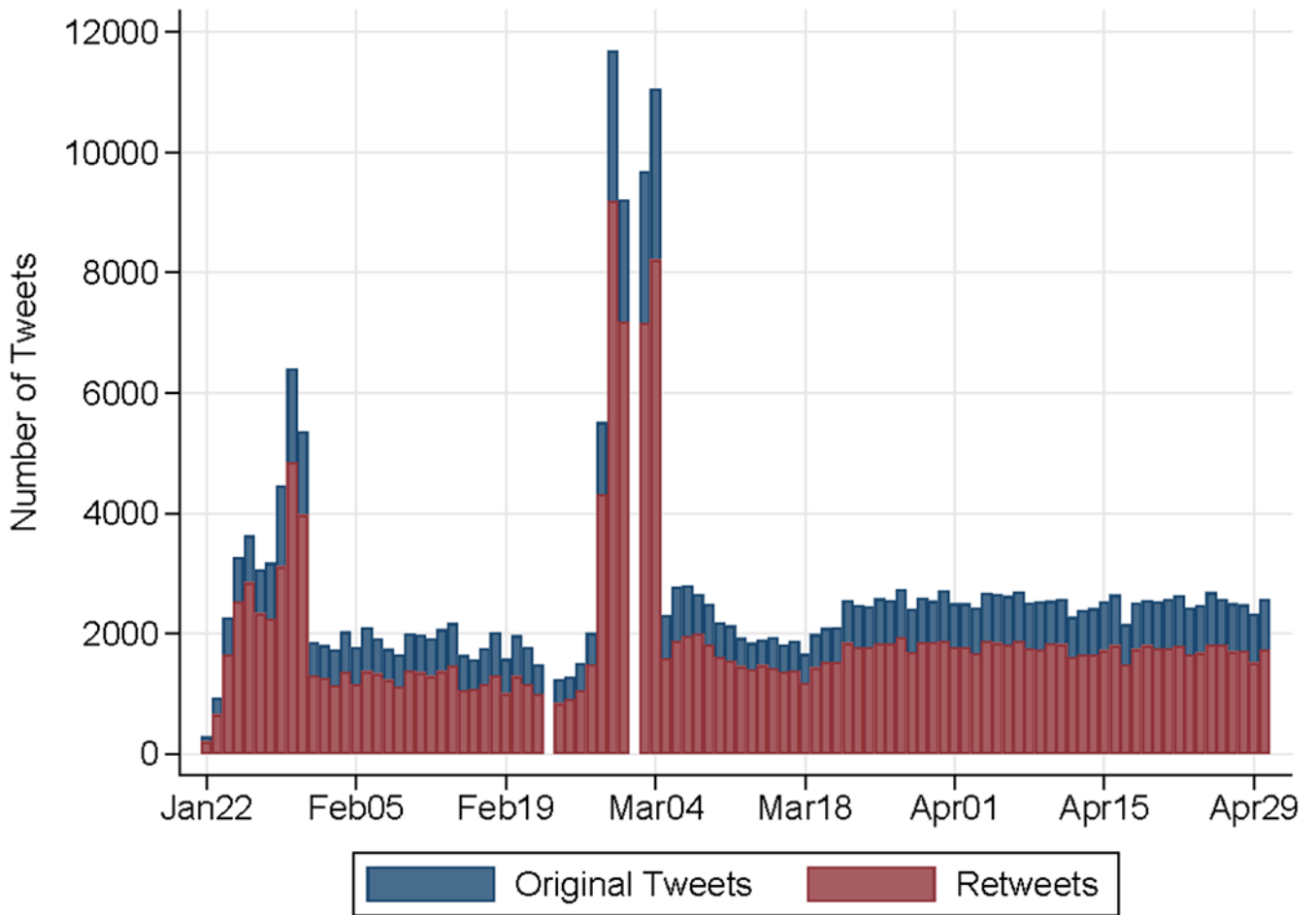


Figure 1. Number of tweets and retweets by doctors.

Note. Figure shows the number of original tweets (including reply tweets) and retweets made by self-identified doctors over time. We excluded 02/23/2020 and 03/02/2020 due to incomplete data collection.

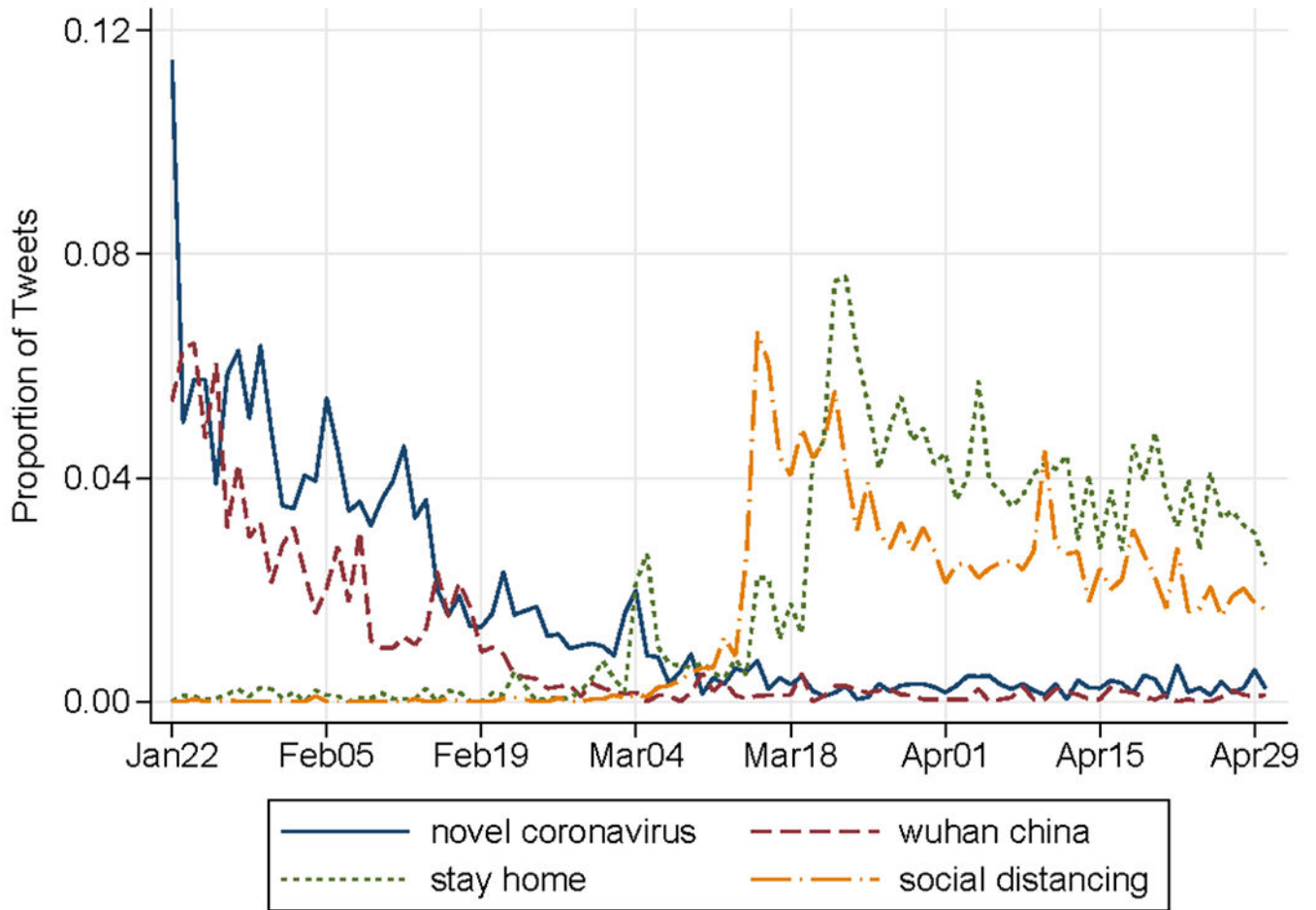


Figure 2. Popularity of selected word pairings over time.
Note. Figure shows the proportion of tweets each day that contain selected common word pairings. We include the entire sample of English-language tweets by self-identified doctors (n = 265,412).

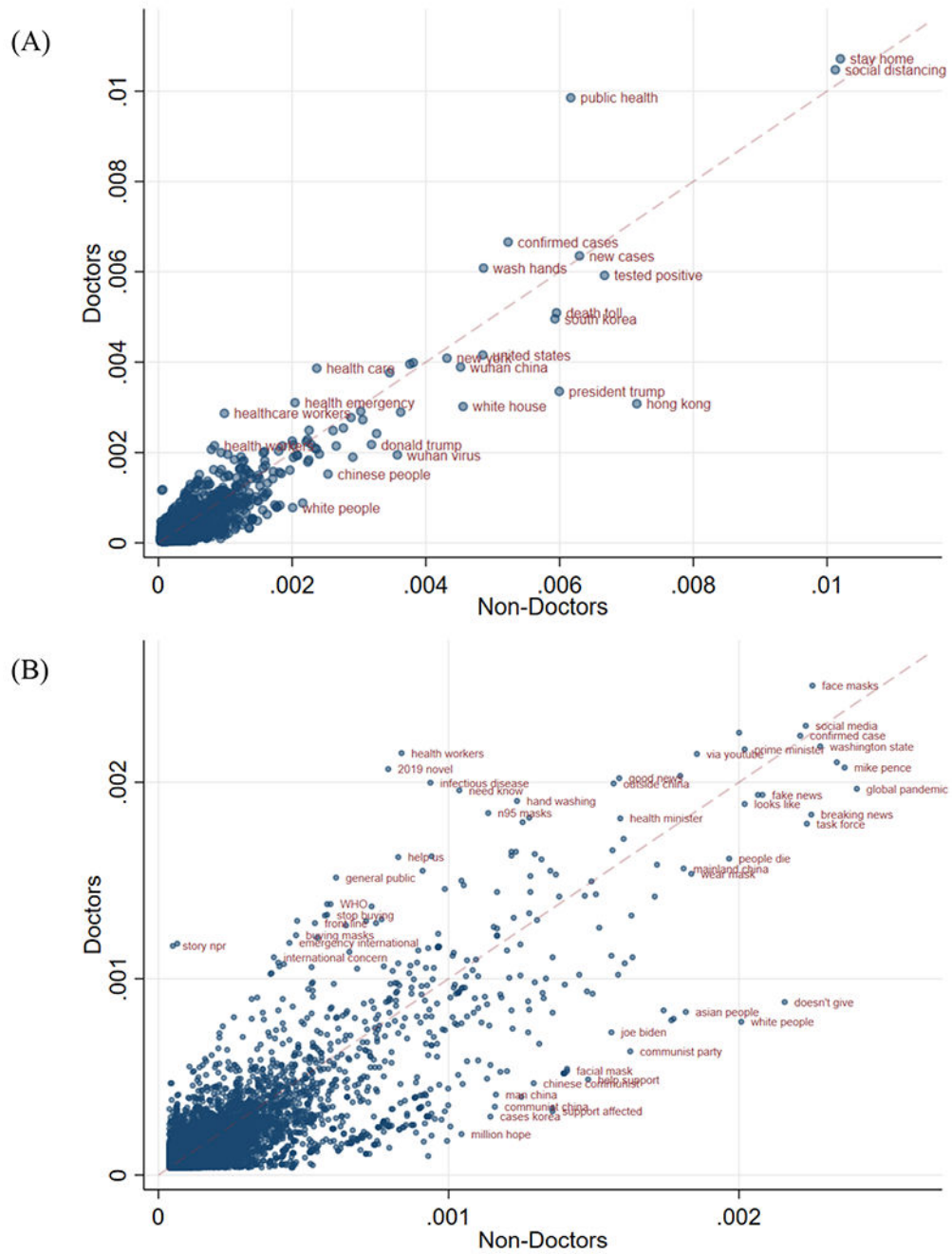


Figure 3. Comparison of word pairings between doctors and non-doctors.

Note. Figure shows word pairings appearing in > 10 tweets, plotted based the proportion of tweets by doctors (n = 265,412) and non-doctors (n = 268,301) that include the word pair. We exclude synonyms for COVID-19. Panel A shows the entire universe of word pairings. Panel B is a magnified view of less common terms. Text labels show terms with high prevalences in both groups or large differences between groups.

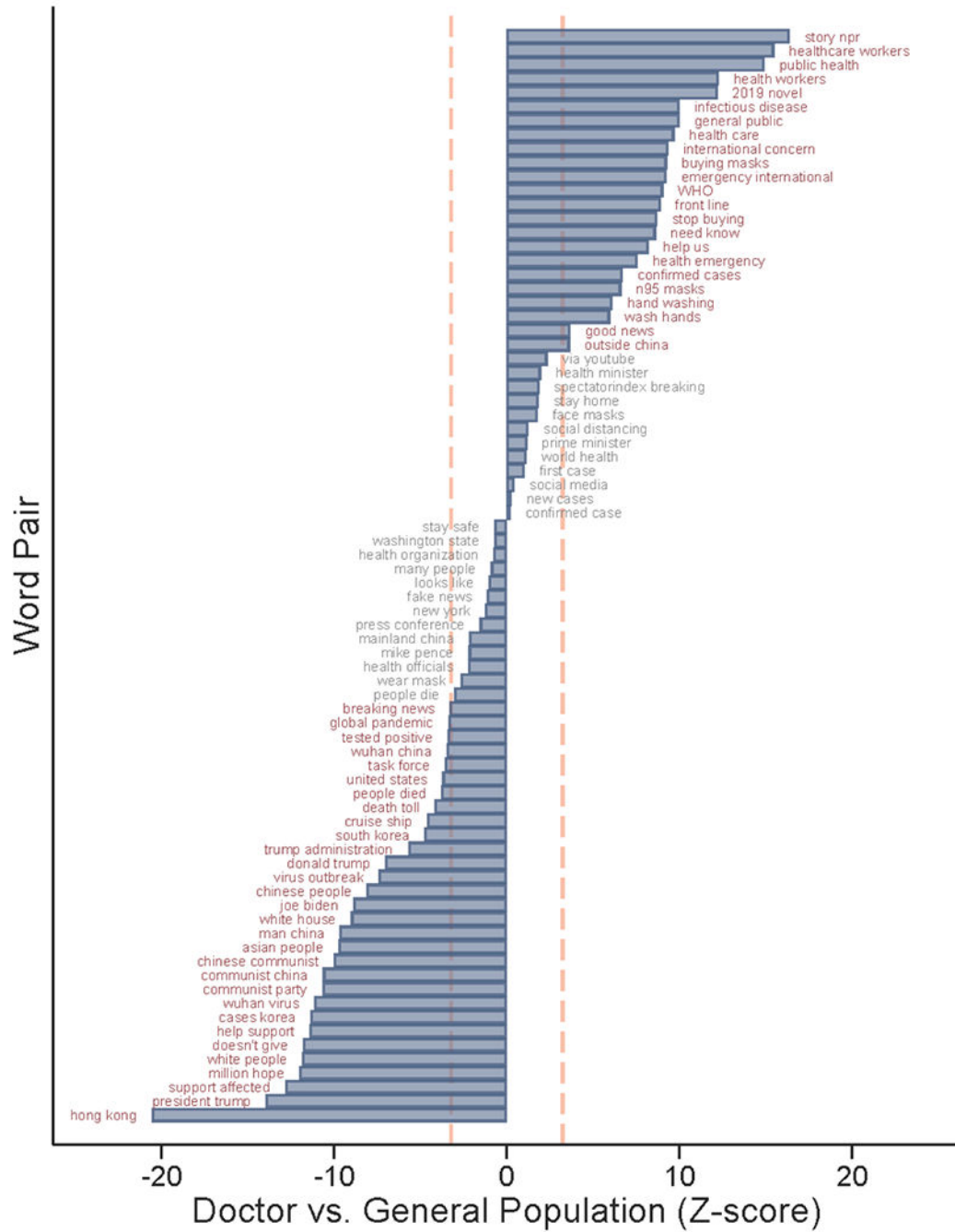


Figure 4. Significant differences in word pairings between doctors and non-doctors.
Note. Figure shows results from tests for statistically significant differences in prevalence for 78 selected word pairings. Y-axis shows word pairings with high prevalence among both doctors and non-doctors or large differences in prevalence between doctors and non-doctors. X-axis shows the Z-score from t-tests comparing word-pair prevalence between doctors and non-doctors, with positive Z-scores indicating significantly higher prevalence among doctor tweets and negative Z-scores indicating significantly higher prevalence among non-doctor tweets. The dashed vertical lines indicate the Bonferroni-corrected significance threshold for

a family-wise error rate of 0.05. Word-pairings reaching Bonferroni-corrected significance are labeled in red; others are labeled in grey.

Table 1.
Sample Characteristics.

	Full Population	Doctor Population	Non-Doctor Sample
English-language tweets	68,108,441	265,412	268,301
Original tweets	15,179,051	75,713	58,708
Retweets	52,929,390	189,699	209,593
Original/Retweet	22.2%/77.7%	28.5%/71.5%	21.9%/78.1%
With location	45,879,039	219,694	180,119
% with location	67.4%	82.8%	67.1%
Number of users	19,664,145	43,877	228,062
With location	13,230,150	34,959	153,841
% with location	67.3%	79.9%	67.4%

Note. Table shows counts for doctors' tweets and a random sample of non-doctor tweets drawn from the general Twitter population. We limit to English-language tweets. The category of original tweets includes reply tweets.

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