

Exploring public perceptions of the COVID-19 vaccine online from a cultural perspective: Semantic network analysis of two social media platforms in the United States and China

Chen Luo ^{a,*}, Anfan Chen ^b, Botao Cui ^c, Wang Liao ^d

^a School of Journalism and Communication, Tsinghua University, Haidian District, Beijing, China

^b School of Journalism and Communication, Chinese University of Hong Kong, Shatin, Hong Kong, China

^c New China Asset Management Company, Chaoyang District, Beijing, China

^d Department of Communication, University of California, Davis, CA, United States

ARTICLE INFO

Keyword:

COVID-19

Vaccine

Social media

Cultural characteristic

United States

China

ABSTRACT

The development and uptake of the COVID-19 (coronavirus disease 2019) vaccine is a top priority in stifling the COVID-19 pandemic. How the public perceives the COVID-19 vaccine is directly associated with vaccine compliance and vaccination coverage. This study takes a cultural sensitivity perspective and adopts two well-known social media platforms in the United States (Twitter) and China (Weibo) to conduct a public perception comparison around the COVID-19 vaccine. By implementing semantic network analysis, results demonstrate that the two countries' social media users overlapped in themes concerning domestic vaccination policies, priority groups, challenges from COVID-19 variants, and the global pandemic situation. However, Twitter users were prone to disclose individual vaccination experiences, express anti-vaccine attitudes. In comparison, Weibo users manifested evident deference to authorities and exhibited more positive feelings toward the COVID-19 vaccine. Those disparities were explained by the cultural characteristics' differences between the two countries. The findings provide insights into comprehending public health issues in cross-cultural contexts and illustrate the potential of utilizing social media to conduct health informatics studies and investigate public perceptions during public health crisis time.

1. Introduction

Vaccination is one of the most critical components of public health programs and significantly contributed to inhibiting the prevalence of infectious diseases (Habibabadi and Haghghi, 2019). Currently, the rapid development and distribution of COVID-19 vaccines are global imperative to restrain the worsening of the COVID-19 pandemic (Graham, 2020). As of July 26, 2021, the COVID-19 pandemic is responsible for over 0.19 billion confirmed cases and nearly 4.2 million deaths (World Health Organization, 2021). Meanwhile, more than 200 COVID vaccine candidates are under development (World Health Organization, n.d.). Several vaccines have been rolled out in some countries (e.g., the United States, China, the United Kingdom) for the most susceptible groups. Some people are longing for the rapid development and distribution of COVID-19 vaccines for achieving sufficient herd immunity to terminate this grave global health predicament (Graham, 2020; Kaur and Gupta, 2020). Nevertheless, a considerable number of people

* Corresponding author.

E-mail address: luoc18@mails.tsinghua.edu.cn (C. Luo).

are hesitant to get vaccinated and even express antagonism, according to several large-scale surveys (Lazarus et al., 2021; Malik et al., 2020; Murphy et al., 2021; Ruiz and Bell, 2021).

Social media has been increasingly adopted as a major means for many people to share and seek health-related information (Habibabadi and Haghghi, 2019; Xu, 2019). On the one hand, social media serves as an ideal signal tower, helps researchers identify public opinions and perceptions of health issues (Luo et al., 2021; Rains, 2020). Investigating public perceptions through social media content is a cost-effective way. It can unravel more authentic and pluralized opinions compared to traditional public opinion surveys (Henrich and Holmes, 2011). On the other hand, online vaccine information is a mixture of scientific evidence, advocacy, misinformation, and even conspiracies (Dunn et al., 2017). People's exposure to various kinds of information is associated with their succeeding vaccination attitudes and intentions (Dunn et al., 2017; Xu, 2019). These backgrounds advocate examining public perceptions toward vaccines online, which undoubtedly benefits researchers and public health practitioners in excavating public concerns about vaccines, and further assisting the design of effective social media-based vaccination persuasive strategies.

Following the vein, this study aims to delve into social media platforms to explore public perceptions of the COVID-19 vaccine. Additionally, we incorporate the cultural perspective to further probe the relationship between public perceptions and cultural characteristics. Culture is a largely overlooked ingredient in preceding studies around public health issues (Dutta, 2007; Kreuter and McClure, 2004). However, cultural characteristics are directly or indirectly related to the acceptance and compliance of health promotion programs (Pasick et al., 1996). Understanding culture is indispensable to comprehend the health behaviors of specific groups (Kreuter and McClure, 2004). Although the most recent COVID-19 vaccine research includes several transnational studies (e.g., Lazarus et al., 2021), the researchers barely scratched the surface of culture by comparing results from a handful of countries rather than operating in-depth interpretations combining countries' cultural backgrounds.

Specifically, the United States and China, as two countries pretty disparate in culture (Tang and Peng, 2015) and vaccination intention (Lazarus et al., 2021), were selected as our analytical objects. We applied the culture-based framework and utilized the semantic network analysis (SNA) to discover prominent discussion themes toward the COVID-19 vaccine on the two countries' representative social media platforms. Regarding the findings, we illustrate the thematic differences with cultural theories to situate people's expressions in their corresponding cultural settings. The implications of this study are threefold. Firstly, we intend to exert the strength of social media as a public opinion bonanza to recognize how people perceive the COVID-19 vaccine; this is particularly necessary for the dearth of relevant research on public views of this relatively novel vaccine. Secondly, this culture-based comparative study would forward current scholarship on the connection between public opinion and culture, also demonstrates social media's efficacy in conducting multicultural public health studies. Thirdly, our endeavor aims to present a comprehensive landscape of public perceptions of the COVID-19 vaccine rather than focusing on specific aspects (e.g., vaccine misinformation, vaccine hesitancy, vaccine promotion). We believe our attempts are conducive to understanding the state of mind of the general population. The most remarkable novelty of the current work is examining public perceptions comparatively through a cultural perspective instead of targeting one specific country. We believe our endeavors contribute to a deeper understanding of the opinion climate encompassing the COVID-19 vaccine across countries, also provide a preliminary reference to future transnational health informatics studies.

In line with our research objectives, the rest of this paper is organized as follows. In sections two to four, we first outlined studies concerning vaccine discussions on social media platforms, especially the latest progress of COVID-19 vaccine perceptions exploration performed on social media derived from the automated text analysis approach. The cultural perspective and analytic objects follow. Section five describes data sources and the SNA method leveraged in this study. In section six, we demonstrate the detailed results. We also discuss our findings from the cultural perspective and the remaining limitations in sections seven and eight.

2. Vaccine themes on social media

People are more and more frequently turning to social media for vaccine information (Massey et al., 2016; Shoup et al., 2019). Social media, in turn, can influence users' knowledge and attitudes about vaccination (Lama et al., 2019). Generally speaking, social media's vaccine information can be split into two crude categories, namely the pro-vaccine theme and the anti-vaccine theme (Featherstone et al., 2020a; Ruiz and Barnett, 2015). The pro-vaccine strand emphasizes vaccines' effectiveness in preventing diseases, while the anti-vaccine strand usually revolves around adverse vaccine reactions, potential detrimental impacts, misinformation, or conspiracy theories (Featherstone et al., 2020b; Nan and Madden, 2012). Deiner et al. (2019) pointed out that anti-vaccine discourses are always deficient in scientific evidence but more prevailing than pro-vaccine discourses. Xu and Guo (2018) further pointed out that online anti-vaccine speech was more likely to garner attention because people are predisposed to share and comment on them than pro-vaccine speech. Considering the prevalence of anti-vaccine expressions online, a large number of scholars endeavored to explore the anti-vaccine landscape on social media (e.g., Johnson et al., 2020) and how to combat social media vaccine misinformation (e.g., Zhang et al., 2021).

Researches concerning specific kind of vaccine provide a more inclusive picture of vaccine themes. For instance, Henrich and Holmes (2011) used news articles' online comments to unearth themes regarding the H1N1 vaccine. The major themes include fear of H1N1, media responsibility, government competency, government trustworthiness, and so on. Lama et al. (2019) conducted HPV vaccine research on Reddit. They found that the most popular topics were HPV vaccine political debate, followed by HPV disease and immunity, the HPV vaccine schedule, and HPV vaccine side effects. A topic modeling analysis based on discussion forums excavated six themes pervaded in vaccine-related discussions, including prominent figures, reports of side reactions, the duration of vaccine immunity, eradication of diseases through vaccination, risk assessments for child vaccination, and trust or distrust in the medical industry (Skeppstedt et al., 2018). Featherstone et al. (2020b) exploited the Twitter corpus to explore childhood vaccination themes. Results revealed that HPV vaccination as a preventative measure was the most prominent theme; subsequent themes included MMR vaccine-

autism link and measles outbreak rates.

When it comes to exploring public perceptions of COVID-19 vaccines on social media, the most prominent approach is examining public opinion with the power of topic modeling and automated sentiment analysis. For example, [Hu et al. \(2021\)](#) investigated the spatiotemporal trends of public perception and sentiment toward COVID-19 vaccines with the help of sentiment analysis, emotion analysis, topic modeling, and word cloud mapping. [Saleh et al. \(2021\)](#), [Lyu et al. \(2021\)](#), and [Guntuku et al. \(2021\)](#) wielded comparable strategies to answer similar questions. This series of studies provide an excellent reference to our work on exerting the advantages of a plethora of automated text analytical techniques. However, we are aware that there still exists space for improvement. On the one hand, the antecedent study failed to illuminate words' associations in their studies. Topic modeling or word cloud merely displays prominent words under specific topics or semantic clusters independently. We desire to employ SNA's associative schema, which is more intuitive, to supplement the underlying isolated schema of the topic modeling approach. On the other hand, most extant studies about COVID-19 are country-specific (e.g., [Gever et al., 2021](#); [Lee et al., 2021](#)), with a heavy focus on the U.S. ([Hu et al., 2021](#)). Our research is one of the few studies that implement a cross-national perspective by emphasizing the role of culture.

In summary, former scholars' efforts illustrate the appropriateness of adopting social media data to scrutinize public perceptions of vaccines, along with the potential of automatic text analysis, which outperforms manual coding in processing large-scale data. Moreover, previous attempts often relied on a single platform or particular context to outline public perception toward vaccines, leaving a research space for cross-cultural public perception comparison. Since social media carries voluminous expressions, reflecting the public's views and attitudes about vaccines, we believe our effort could portray the current opinion contour of the COVID-19 vaccine in two countries and inform concerted, tailored health communication efforts to raise the COVID-19 vaccine uptake rates in the two cultures.

3. Cross-country perspective and cultural differences

Culture has been a seriously overlooked component in health communication studies. Most health promotion efforts linger on the individual level ingredients (e.g., cognitive process, behavioral logic) but are insensitive to the sociocultural-economic contexts within which health experiences are inhabited ([Dutta, 2007](#)). [Kreuter and McClure \(2004\)](#) argued that a group's cultural characteristics might directly or indirectly connect with its health-related priorities, decisions, and behaviors. Thus, culture functions as a pivotal audience-segmentation variable. Bearing culture in mind also enhances the effectiveness of health communication efforts by informing a reasonable arrangement of source, message, and channel factors.

Although examining culture's role in health communication is still in its infancy, some studies have presented the value of recognizing culture's roles. For example, [Pan et al. \(2020a\)](#) carried out an online survey concerning HPV vaccination intention in the United States and China. The results illustrated cross-cultural differences in how contradictory information exposure and social norms affect intentions to receive the HPV vaccine in the two countries. Americans are less tolerant of uncertainty so that contradictory message exposure significantly diminishes American respondents' vaccination intentions. In contrast, injunctive norms were positively associated with Chinese respondents' vaccination intention due to the collectivistic culture's profound influence. [Tang and Peng's \(2015\)](#) research on health reporting in the United States and China revealed significant reporting differences in controllability attribution, temporal orientation, statistics usage, and citing authorities. Those disparities can partly be attributed to the two countries' cultural traits, including individualism versus collectivism, long- and short-term orientation, and power distance.

Enlightened by the aforementioned, we take the cultural sensitivity approach as a reference. [Dutta \(2007\)](#) conceptualized culture as a relatively stable set of shared values, beliefs, and practices within a community, which can be a criterion to differentiate a community from another. The hidden cultural dimensions include individualism-collectivism, power distance, and so on. Adhering to the cultural sensitivity approach implies comprehending specific cultural needs of given communities and anchoring health-relevant information in a particular cultural context. Only in this way can a researcher recognize certain health communication phenomena' underlying logics. Accordingly, Hofstede's cultural dimensions model can be a concrete guide for applying the cultural sensitivity approach ([Hofstede, 2011](#); [Hofstede and Hofstede, 1993](#)). [Hofstede \(2011\)](#) also views culture as a differentiating indicator for groups. The four fundamental pillars of Hofstede's model include power distance, uncertainty avoidance, individualism versus collectivism, and masculinity versus femininity. These four dimensions are essential and enduring, representing a given cultural group's collective mindset, which affects affiliated individual's daily perceptions and behavioral patterns. According to [Hofstede \(2011\)](#), power distance stands for how the less powerful members accept and expect that power is distributed unequally. Uncertainty avoidance denotes a society's tolerance for ambiguity and variability. Individualism versus collectivism alludes to the degree to which individuals in a community are integrated into groups. Masculinity versus femininity reflects the distribution of values between gender in society. Country comparisons are realizable based upon the identified dimensions, such as the "Compare Countries" function in Hofstede Insights ([Hofstede Insights, 2021](#)) website derived from the cultural dimensions model.

4. Why the United States and China?

This study picks two countries - the United States and China, as analytic objects. First of all, the two countries all experienced a crucible owing to the COVID-19 pandemic. China was once the epicenter of the COVID-19 outbreak. However, the Chinese government adopted numerous effective preventive and control measures to mitigate the contagion, making China one of the world's first countries to tame the spread of COVID-19 ([Luo et al., 2020](#)). The United States also suffered huge impacts from COVID-19, but its countermeasures did not meet public expectations. [Tanne \(2020\)](#) argued that the U.S. government downplayed the pandemic's urgency at first, let alone worked out an efficient national plan to combat the COVID-19. The sluggish counteracting resulted in a surge in

infection rate and mortality rate within a short time. Things turned better after the new president took office in January 2021, mainly credited to the Biden administration's firm battle plan, mandatory requirements, and scientific precautions (Siemaszko, 2021). As two superpowers, the United States and China devote themselves to the COVID-19 vaccine development, manufacture, and deployment. The most remarkable instances include the mRNA vaccine manufactured by the American pharmaceutical corporation *Moderna* (Haque and Pant, 2020) and the inactivated vaccine produced by the Beijing-based biotechnology company *Sinovac* (Tan, 2021).

Second, the U.S. and China show significant differences in cultural characteristics. The Hofstede indexes exhibit clear distinctions on power distance (for the U.S.: 40, for China: 80), individualism versus collectivism (for the U.S.: 91, for China: 20), uncertainty avoidance (for the U.S.: 46, for China: 30) between the two countries (Hofstede Insights, n.d.). In addition, prior studies illustrated the rationale and potential to compare China and the U.S. based on the culture-sensitive approach in the health communication context (e.g., Ding and Zhang, 2010; Pan et al., 2020a; Tang and Peng, 2015). In this vein, it is viable for us to compare public perceptions of COVID-19 vaccines under the cross-country perspective and infer the reasons behind perception differences from the cultural dimensions. All the aforementioned informs our research questions.

RQ1: What central themes about the COVID-19 vaccine emerged on American and Chinese social media platforms?

RQ2: Are there any thematic differences exist between the two countries' public perceptions of the COVID-19 vaccine on social media? If any, do they reflect cultural differences?

Jiang et al. (2018) proposed that sentiment analysis is often bound up with thematic analysis because it facilitates understanding attitudes toward an attitudinal subject. Sentiment analysis is particularly indispensable in vaccine studies because anti-vaccine sentiment has prevailed online for a long time (Featherstone et al., 2020b). Whether the negative sentiment still plays the dominant role in the COVID-19 vaccine context needs empirical validation. Hence, we put forward the last question.

RQ3: What's the sentiment distribution toward the COVID-19 vaccine on American and Chinese social media platforms, respectively?

5. Methods

This study employs SNA to explore the hidden themes of social media discussions, through which the researchers can grasp the principal dimensions of public perceptions toward the COVID-19 vaccine. SNA is a popular branch in computerized content analysis, which can supplement traditional human-coded content analysis by enhancing reliability and overcoming the crude categorization of the analytic framework (Danowski, 1993; Doerfel and Barnett, 1999). Rooted in the cognitive paradigm and the linguistic theory of frame semantics, SNA extracts latent semantic structures by analyzing concept associations (Calabrese et al., 2019). Therefore, we can identify the importance of words in an interrelated approach instead of an isolated perspective and comprehend discussion themes arisen from emerging clusters of concepts (Featherstone et al., 2020b; Li et al., 2019; Smith and Parrott, 2012).

5.1. Data collection

Social media is suitable for conducting comparative studies and enables researchers to obtain miscellaneous digital traces (including multilingual social media posts) unobtrusively (van Atteveldt and Peng, 2018). Here, we select Twitter as the representative of American social media platforms for two reasons. On the one hand, Twitter is a popular social media platform with a large user base and carries heated discussions about vaccines and vaccination (Featherstone et al., 2020a; Featherstone et al., 2020b). On the other hand, Twitter has been a social signal tower amid the COVID-19 health crisis. Heterogeneous users actively expressed their concerns and perceptions on Twitter, making it an outstanding field for infodemiology study (Chandrasekaran et al., 2020; Saha et al., 2020).

Likewise, Weibo, one of China's leading social media service providers, was chosen as the representative of Chinese social media. Weibo has been lauded as the Chinese equivalent of Twitter. It also has numerous users and contributes to the rise of civil society and the public sphere in China (Lu and Qiu, 2013). During the COVID-19 period, Weibo serves as an information aggregation platform where people can find epidemic-related information quickly and effectively (Huang et al., 2020). Furthermore, Weibo's user-generated posts have the potential to predict COVID-19 infected cases (Shen et al., 2020), indicate public reactions as well as psychological conditions (Su et al., 2020).

The time range was designated from December 1, 2020, to February 20, 2021. According to statistical results from the [Our World in Data \(n.d.\)](#), the COVID-19 vaccine doses administered per 100 people in the United States and China were close to 0.1 on December 1, 2020, which means the vaccination process in the two countries were at the initial stage. The closing date was set as the day before our formal analysis.

We utilized an advanced web scraping tool named *Twint* ([twintproject, n.d.](#)), which can bypass Twitter's official API limits to get all eligible tweets under specified search conditions. Following the work of Featherstone et al. (2020b), the search terms are comprised of "vaccine," "vaccination," "shot," "immunization," "immunisation" in combination with COVID-19 terminologies "COVID-19," "coronavirus," and "COVID." We only kept the original tweets (i.e., discarded retweets and quotes) to eliminate replicated and redundant information, which may dilute the genuine public perceptions (Calabrese et al., 2020). After excluding non-English tweets, duplicates, and tweets sent outside the United States, 756,118 tweets were preserved for further analysis. Weibo posts were retrieved in a similar approach. An automated web crawling platform named *SocialSensor* ([SocialSensor, n.d.](#)) was adopted to collect qualified posts. Given the unique feature of Chinese words, four search terms were assigned, including "COVID-19 vaccine," "COVID-19 pneumonia vaccine," "coronavirus vaccine," and "SARS-CoV-2 vaccine" (see [Supplementary Data 1](#) for the Chinese meaning of the search terms). 362,950 Weibo posts were kept after filtering.

5.2. Analytic strategies

Drew on previous SNA studies (Calabrese et al., 2019; Calabrese et al., 2020; Featherstone et al., 2020a; Featherstone et al., 2020b; Kwon et al., 2009; Ruiz and Barnett, 2015), we analyze the Twitter and Weibo corpus in the subsequent three steps.

First of all, we performed preprocessing on the two corpora, including converting the posts to lowercase for term unification, removing URLs, stopwords, punctuations, special characters, and mentioned users. We also merged synonyms and ruled out syntactic function words for accuracy (relevant terms are displayed in [Supplementary Data 1](#)). Lemmatization was conducted afterward, which outperformed stemming for it would not collapse derivationally related words (e.g., “organized” to “organize” rather than “organ”) (Maier et al., 2018). Tokenization was adopted on the processed corpora; words with frequencies above the mean frequency in each corpus (mean frequency of the Twitter corpus: 100.01, mean frequency of the Weibo corpus: 112.14) were saved in the analysis. Two widely used natural language packages named spaCy ([spaCy, n.d.](#)) and jieba ([fxsjy, n.d.](#)) were applied to handle the tweets and Weibo posts in the Python programming environment.

In the second step, we implemented semantic matrices generation from the processed corpora. Danowski (1993) argued that word-pair link strength could be operationalized as the number of times each word occurs with another when it comes to co-occurrence measurement. Miller (1956) and Cowan (2016) congruously suggested that the number of chunks a person can process in memory is five. Hence, words that occurred within a five-word window were considered linked, and the co-occurrence frequency of each word pair was accumulated. This task was also fulfilled in Python.

In the third step, an open-source network analysis software Gephi was used to visualize the semantic networks (Bastian et al., 2009). Given our corpora's large size, the top 100 words by frequency were included in the network visualization. We further carried out modularity analysis in Gephi to detect semantic clusters and calculated network statistical indicators to measure words' importance. Three measures were considered following Hanneman and Riddle's (2005) suggestions. Network density is the sum of edges divided by the number of all possible edges, representing how intertwined the words are. Degree refers to the number of edges connecting each word, which is a straightforward way to assess each word's centrality. Eigenvector centrality is another way to gauge centrality by finding the most central words based on the network's overall structure. These three network evaluation metrics were widely used in former semantic network studies (Calabrese et al., 2020; Featherstone et al., 2020a; Featherstone et al., 2020b).

Sentiment analysis can unveil the overall attitudes (positive, negative, or neutral) toward the COVID-19 vaccine. Also, sentiment analysis is crucial to capture the public's reaction towards an emerging infectious disease (Albahli et al., 2021; Samuel et al., 2020). We selected two automated sentiment analysis tools for the posts. The LIWC (Linguistic Inquiry and Word Count) reads English texts and counts the percentage of emotional words (Tausczik and Pennebaker, 2010). It has been proved as a powerful tool in analyzing tweets'

Table 1
The top 30 central words in the overall semantic networks.

No.	Twitter			Weibo		
	Word	Degree	Eigenvector centrality	Word	Degree	Eigenvector centrality
1	covid	5848	0.049	vaccine	8511	0.066
2	vaccine	5848	0.049	covid	8190	0.066
3	vaccination	5717	0.049	vaccinate	7459	0.063
4	shot	5574	0.049	epidemic	7063	0.062
5	coronavirus	5283	0.047	china	6709	0.060
6	people	5242	0.048	america	6400	0.059
7	health	4802	0.046	coronavirus	6223	0.058
8	shoot	4800	0.045	country	5618	0.056
9	need	4749	0.046	pneumonia	5491	0.055
10	new	4736	0.045	global	5129	0.053
11	work	4587	0.045	work	4977	0.052
12	today	4555	0.044	uk	4909	0.052
13	time	4460	0.044	time	4889	0.052
14	day	4444	0.044	company	4667	0.050
15	know	4433	0.044	user	4621	0.049
16	year	4349	0.044	virus	4562	0.049
17	news	4308	0.043	scheme	4354	0.049
18	receive	4284	0.043	situation	4279	0.049
19	week	4268	0.043	market	4203	0.047
20	good	4233	0.043	government	4124	0.047
21	use	4215	0.043	provide	4096	0.047
22	come	4164	0.043	coverage	4068	0.046
23	help	4163	0.043	shot	4063	0.046
24	state	4153	0.043	health	3979	0.045
25	vaccinate	4126	0.042	relevant	3967	0.046
26	think	4119	0.042	influence	3918	0.046
27	dose	4108	0.042	test	3892	0.045
28	want	4094	0.042	beijing	3866	0.044
29	start	4053	0.042	international	3841	0.045
30	look	3887	0.041	world	3807	0.044

Note. Words from the Weibo corpus are translated into English for ease of comparison. All words are presented in lower case.

discrete emotions (Margolin and Liao, 2018) and other kinds of online posts (Pan et al., 2020b). For the Weibo corpus, the TextMind software developed by the Chinese Academy of Sciences works as a substitute for LIWC in analyzing Chinese social media posts with enough reliability and validity (Gao et al., 2013). It has been applied to analyze rumor-related Weibo posts during the COVID-19 pandemic (Song et al., 2021).

6. Results

6.1. Semantic networks

In congruence with extant studies (Calabrese et al., 2019; Featherstone et al., 2020b), the 30 most central terms based on eigenvector centrality and degree were presented in Table 1. This is an elementary quantitative description of word usage in the two social media platforms, which manifests preliminary differences between public perceptions of the two countries.

There are 5865 words above the mean word frequency in the Twitter corpus, and they construct a network with 1,886,281 edges. The density of the whole network is 0.110. Regarding the Weibo corpus, 9081 words have a frequency larger than the mean value, with 1,913,737 edges connecting them. The network density is 0.047, which means the Weibo network is loosely interconnected than the Twitter network. As shown in Table 1, only a few overlaps exist between central words on the two platforms. Apart from the search terms (i.e., COVID, vaccine, vaccination, shot, coronavirus), the most common words in tweets are *people*, *health*, *shoot*, *need*, and *new*. In contrast, the most frequent terms in Weibo posts are *epidemic*, *China*, *America*, *country*, and *pneumonia*.

Figs. 1 and 2 exhibit the semantic networks of Twitter discussions and Weibo discussions using the ForceAtlas2 layout configuration embedded in Gephi. The top 100 words by frequency in each corpus were retained for a concise and clear visualization. Besides, search terms were removed from the final networks because predominant words are highly likely to link all the other words together into a single group, which may distort the results (Jiang et al., 2018). For clarity, we solely present edges with a weight above the average edge weight. Complete semantic networks are exhibited in [Supplementary Data 2](#). The label size for each node denotes the eigenvector centrality of the corresponding word. A thicker edge indicates a stronger co-occurrence relationship between two words. After the modularity analysis, each semantic subcluster is rendered by a specific color. We present a summarization in [Table 2](#), containing each subcluster's theme, top word associations, and percentage share of the network. It is noteworthy that the size of all words is very close. This is due to the massive data in our analysis. In other words, it is easy to find a co-occurrence relationship between any two words in a five-word span among large-scale corpus. Consequently, the eigenvector centrality values of all words are relatively small in a densely

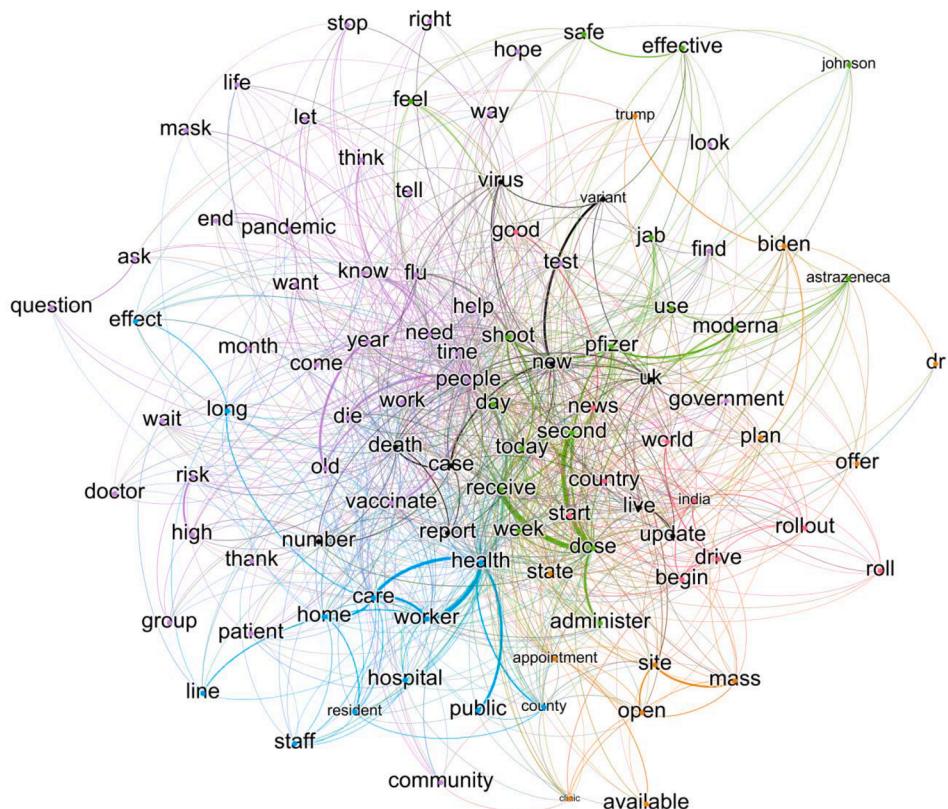


Fig. 1. The semantic network visualization of COVID-19 vaccine discussions on Twitter. Note. All words are presented in lower case. Only edges with weights above the average weight (182,766) are presented.

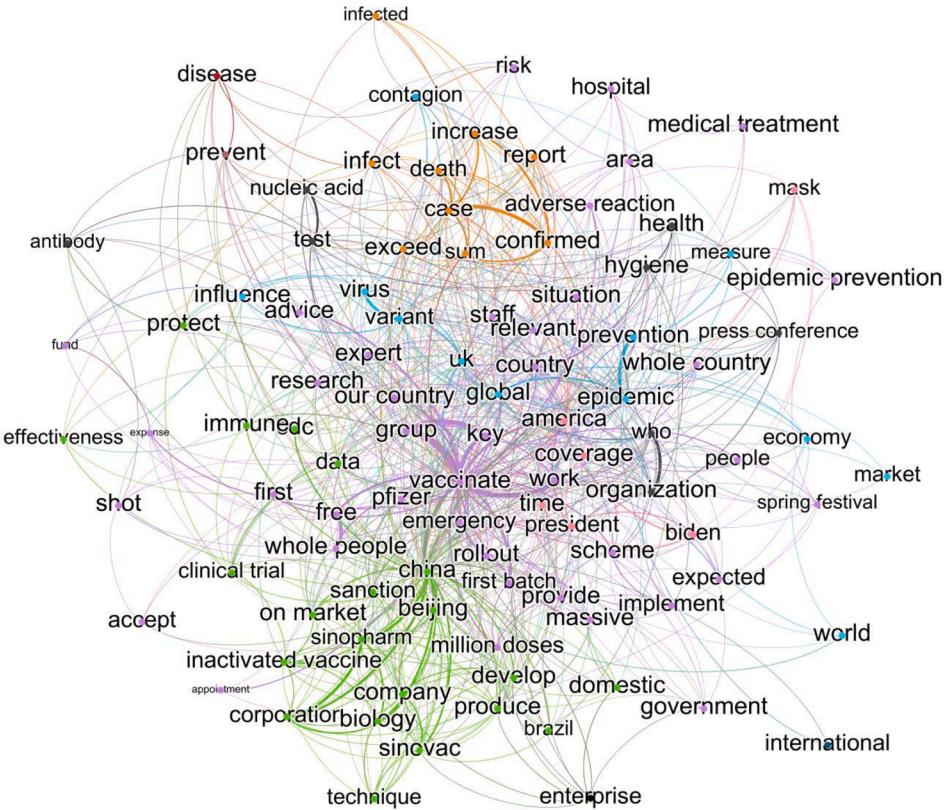


Fig. 2. The semantic network visualization of COVID-19 vaccine discussions on Weibo. Note. Words from the Weibo corpus are translated into English for ease of comparison. Some Chinese words may correspond to two English terms. All words are presented in lower case. Only edges with weights above the average weight (503.038) are presented.

connected network.

In Fig. 1, there exist 4945 edges. The network density is 0.999. The average degree is 98.90, and the average weighted degree is 18,075.60. Edges represent co-occurrence relationships between words. Network density measures how many edges between words exist compared to all potential edges. The average degree denotes the average number of edges per word in the overall semantic network (Hanneman and Riddle, 2005). The average weighted degree considers the edge weight, describing the average sum of the weights of edges connected to a word. Thus, a high network density means that words are closely related to each other. Similarly, a high average degree value hints that words are densely interrelated. The average weighted degree value implies each word in the network has a relatively high co-occurrence frequency with other words. These metrics are often employed when comparing different networks. Therefore, we offer a further explanation after presenting the semantic network of Weibo. Six themes were discerned in the Twitter semantic network. The largest one is vaccine promotion and anti-vaccine discourses (39.0% of the network), focusing on both benefits of vaccination and suspicions toward the COVID-19 vaccine. Some users quoted professional voices (such as Dr. Anthony Fauci) to encourage people to get vaccinated and accentuate the vaccine's preventive effects. On the contrary, another clique employed extreme cases to emphasize the adverse effects, including elderly people who died after inoculating. Personal vaccination experience followed as the second-largest theme (17.0% of the network), mainly about sharing vaccination experience and feelings, such as "I received my second dose of the Pfizer-made vaccine today and I feel good." The third cluster revolves around the vaccination priority groups (12% of the network), including particular policies toward healthcare workers and other medical staff working in the front line. Another theme with comparable size (12% of the network) is relevant to the government's constantly updating vaccination policies and measures, such as opening new vaccination sites, the Biden administration's evolving control plans, and other kinds of vaccination efforts. The next theme talks about tremendous challenges from COVID-19 variants (10% of the network), primarily associated with the highly contagious mutant virus in the U.K., including its dire consequences on increasing confirmed and death cases sharply. The last cluster centers on vaccination progress worldwide (10% of the network); one of the most typical examples is India's massive vaccination drive.

When it comes to Fig. 2, there exist 4898 edges. The network density is 0.989. The average degree is 97.90, and the average weighted degree is 49,277.64. Compared to Fig. 1, the lower network density and average degree mean that words in Weibo's semantic network are more loosely connected than Twitter. However, its average weighted degree is larger than Twitter's semantic work, which implies an individual word in Weibo's semantic network is more frequently co-occurred with other words. The most notable theme (40.0% of the network) is vaccination policies and priority groups, dealing with the implementation of national free vaccination

Table 2

The summary output of modularity analysis of two semantic networks.

Network	Theme	Top associations	Association count	Cluster color	Share of the network (%)
Twitter	Vaccine promotion and anti-vaccine discourses	old	year	5065	Purple
		die	people	5029	
		people	vaccinate	4341	
		high	risk	3881	
		flu	year	3592	
	Personal vaccination experience	dose	receive	11,012	Green
		dose	second	9420	
		administer	dose	4839	
		dose	pfizer	3488	
	Vaccination priority groups	moderna	pfizer	3408	
		health	worker	7695	Blue
		care	health	6365	
		health	public	4875	
		care	worker	4618	
	Government's constantly updating vaccination policies	care	home	3378	
		mass	site	3846	Orange
		open	site	2560	
		biden	trump	1490	
		biden	plan	1357	
	Challenges from COVID-19 variants	mass	open	1347	
		new	variant	4760	Black
		case	new	2842	
		case	death	2620	
		death	report	1916	
	Vaccination progress worldwide	live	update	1698	
		good	news	2461	Red
		drive	world	2311	
		drive	india	1825	
		begin	drive	1784	
	Weibo	india	world	1608	
		group	vaccinate	51,917	Purple
		group	key	33,976	
		work	vaccinate	31,514	
		vaccinate	key	30,439	
	Domestic vaccines' research and development	free	whole people	23,308	
		sinopharm	corporation	19,861	Green
		china	sinopharm	18,959	
		china	corporation	16,656	
		china	biology	13,960	
	Challenges from COVID-19 variants	china	sinovac	10,997	
		epidemic	prevention	25,975	Blue
		variant	virus	20,294	
		global	epidemic	11,370	
		variant	uk	10,162	
	The global epidemic progress	variant	influence	5227	
		case	confirmed	25,436	Orange
		increase	confirmed	13,302	
		death	case	12,208	
		increase	case	11,630	
	WHO's advocacy and evaluation	confirmed	sum	11,270	
		who	organization	20,943	Black
		nucleic acid	test	14,553	
		health	hygiene	6070	
		press	organization	2417	
	Epidemic development in the United States	conference	test	2043	
		antibody	america	8594	Red
		president	america	7440	
		biden	america	6324	
		time	america	5823	
	coverage	president	biden	5376	
		coverage	america		

Note. Words from the Weibo corpus are translated into English for ease of comparison. Some Chinese words may correspond to two English terms. All words are presented in lower case.

policies, the rollout of vaccines for emergency use, and key groups in the immunization plan. The second-largest theme talks about domestic vaccines' research and development (22.0% of the network). Some typical corporations such as *Sinopharm* and *Sinovac* frequently appear in this cluster. The third theme addresses challenges from COVID-19 variants (13.0% of the network), especially the impacts of the mutant virus in the U.K. on existing preventive measures' effectiveness and the stability of the world economy. The global epidemic progress comes after the third theme (9% of the network), mainly refers to the increasing trend of confirmed and death cases worldwide. The fifth theme is tightly related to the World Health Organization (WHO, see [Supplementary Data 3](#) for all abbreviations and their original forms), concerning WHO's advocacy of nucleic acid and antibody tests as well as WHO's evaluation of Chinese vaccines (8% of the network). The last theme talks about epidemic development in the United States (8% of the network). The most central words in this cluster are *president*, *Biden*, and *America*.

6.2. Sentiment analysis

Sentiment analysis indicates that neutral tweets occupied the largest territory in the Twitter corpus with a percentage of 49.99% ($n = 377,951$), followed by positive tweets (30.62%, $n = 231,507$) and negative tweets (19.40%, $n = 146,660$). In comparison, the majority of Weibo posts are positive (40.64%, $n = 147,521$), followed by neutral posts (37.44%, $n = 135,871$) and negative posts (21.92%, $n = 79,558$).

7. Discussion and conclusion

To echo the research questions and cultural sensitivity approach, we elucidate the results in a comparative way. One of the most remarkable distinctions between the two corpora is personal vaccination experience occupied a large area in Twitter's semantic network. However, Weibo users rarely mentioned self-experience and vaccination feelings. This narrative discrepancy can be partly ascribed to the inherent difference between individualism and collectivism. [Triandis \(2001\)](#) claimed that people from individualist societies are relatively autonomous and independent from groups; they always set their personal goals above the group aims. People in collectivist cultures are likely to have close interactions with their in-groups and prioritize group aims. Furthermore, when integrating individualism versus collectivism into the health communication context, [Lu et al. \(2020\)](#) and [Lu et al. \(2021\)](#) claimed that individualistic cultures endorse self-reliability and personal control over health risks. Contrarily, collectivistic cultures highlight interdependence and external social norms to handle health risks. In this logic, individualists are inclining to make vaccination decisions out of their own will. They also have more freedom to express their thoughts and attitudes on the premise of self-determined health behaviors. For collectivists, they need to be highly embedded into their surroundings. Due to the restrictions from group norms and pressure, they are more likely to hide individualized feelings and dispositional thoughts to keep coherence with others or avoid negative social sanctions. Besides, China's somewhat compulsory group vaccination scheme contributed to this disparity. Xinhua Net once reported that China is administering COVID-19 vaccines to susceptible groups all over the country for a sufficient vaccination rate to avoid the resurgence of the pandemic ([Sun et al., 2021](#)). According to [Ajzen's \(1991\)](#) theory of planned behavior, people's behavior is substantially affected by normative beliefs and subjective norms. It is highly probable for people to follow the perceived social standards and significant others' actions to reach a behavioral decision, which is quite remarkable in collectivistic cultures. This finding coincides with [Pan et al. \(2020a\)](#) research to some degree, which discovered that perceived injunctive norms were positively related to behavioral intention for the Chinese respondents but did not work for the American respondents. To summarize, living in a country deeply influenced by collectivism, Chinese people are prone to follow communal rules and hide self-experience.

Another incongruity resides in the great quantity of anti-vaccination discussions on Twitter, but similar discourse is rare on Weibo. The anti-vaccine narrative on Twitter has been repeatedly accentuated in former studies ([Kang et al., 2017](#); [Kata, 2012](#); [Murphy et al., 2021](#); [Radzikowski et al., 2016](#)). Possible determinants of the anti-vaccine mind include individual-level factors (e.g., vaccination knowledge), group-level factors (e.g., community pressure), and factors from the broader socio-cultural context ([Dubé et al., 2013](#)). We postulate that the flourishing anti-vaccine narrative on Twitter is partly due to American culture's high uncertainty avoidance characteristic. Individuals from high uncertainty avoidance circumstances are likely to feel uncomfortable in the face of ambiguity and transition. One comparative study on HPV vaccination intention corroborated contradictory vaccine messages directly decreased intention among American respondents than Chinese respondents ([Pan et al., 2020a](#)). COVID-19 vaccine is still an innovative therapeutic intervention for human beings; its efficacy and adverse reactions need more scientific tests and continuous monitoring ([Luo et al., 2021](#)). Therefore, people from a culture with less tolerance for uncertainty are probably exuding mistrust, opposition, and psychological resistance toward the new medical invention. Apart from Chinese people's high tolerance for uncertainties, another reason for the lack of anti-vaccine narrative on Weibo could be the strict control of online content in China. Since authorities greatly endorse the COVID-19 vaccination plan, it is hard and less tolerant to post contradictory narratives against the national will ([Xu, 2014](#)).

Users from the two platforms were unanimously concerned about COVID-19 vaccination policies, priority groups, mutant virus, and the epidemic trend of COVID-19 worldwide. But Chinese users paid more attention to international organizations like WHO. Furthermore, the positive tone dominates Weibo posts compared to the overwhelming neutral tone among tweets. We believe the power distance difference between the two countries accounts for this phenomenon. [Perea and Slater \(1999\)](#) summarized that persons from a culture high in power distance tend to have less doubt of authorities. While those from the low power distance culture generally show weaker deference toward authorities. Moreover, preceding studies revealed that paternalistic leadership and vertical guidance are more effective in achieving group goals and evoking ideal performance in cultures with high power distance ([Aycan, 2006](#); [Gelfand et al., 2007](#)). This finding is particularly true when coping with communal risks; people are accustomed to following superiors and accepting the hierarchical structure in a high power distance environment. Chinese people have the disposition to depend on

established agencies and take their assessments as golden standards. For instance, many Chinese social media users were curious about WHO's evaluation results of Chinese-made vaccines' effectiveness. In the meantime, their attention evolved with media coverage and official statistics, such as the fluctuation of confirmed case counts, signals from the government's press conferences. Regarding the predominant positive tone in Weibo scope, former researchers reported that stricter rules always exist in high power distance settings; those rules suppress ordinary people's expression of negative emotions (Grandey et al., 2010; Moran et al., 2013). Our results partially bolster this finding. Chinese social media users may subconsciously control their negative emotional expression under the background of cultural settings. In brief, compared with the American people, the Chinese showed high deference to official institutions and were less likely to express negative sentiments regarding the COVID-19 vaccine issue.

Overall, this study supplements the jigsaw puzzle of the COVID-19 vaccine research by applying a cultural lens to understand differentiated public perceptions toward the same issue. As two countries differ significantly in cultural characteristics defined by Hofstede (2011), the United States and China were selected for comparison. American and Chinese social media users' horizons overlapped with each other on vaccination policies, priority groups, challenges from COVID-19 variants, and global pandemic situation themes. Incongruities dwell in Twitter users' preference for disclosing personal vaccination experience, expressing anti-vaccine attitudes, along with Weibo users' apparent deference to authorities. Moreover, Chinese social media users demonstrated more positive feelings toward the COVID-19 vaccine than their American counterparts. As Dutta (2007) implied, the study of culture provides a fertile ground for understanding health communication phenomena across diverse socio-cultural contexts. The cultural sensitivity approach can always explain a series of discrepancies in the public health field (Tang and Peng, 2015), but we can't subsume all inconsistencies under culture for granted. In a nutshell, we need to respect all the thematic differences because they facilitate the current understanding of public perceptions about a new vaccine, also assist policymakers in devising effective vaccination promotion strategies. However, those differences call for a cautious interpretation. We only made reasonable conjectures on the differences rather than strictly verify how cultural characteristics influence public perceptions in the two countries.

8. Limitations

Findings in our study need to be interpreted within several constraints. Firstly, the speed of development and distribution of COVID-19 vaccines is unprecedented (Graham, 2020). Our study only captured a snapshot of public perceptions toward the COVID-19 vaccine at its initial stage. Thus, more efforts should be made in the future to examine the perception change in a longitudinal perspective, such as possible transformations in public views after momentous events (Calabrese et al., 2020). Secondly, social media footprints' representativeness needs to be pondered (Hilbert et al., 2019). Although vaccination is a hotly discussed issue on social media platforms, whether the insights distilled from social media users' expressions can be generalized to the entire population is clouded in uncertainty. It is sensible for future researchers to retrieve corpus from multiple channels to extend external validity. Thirdly, topic modeling and other machine learning techniques are also widely used in excavating public perceptions. A reliable way to elevate robustness should be comparing the results from semantic network analysis and machine learning approaches.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.tele.2021.101712>.

References

- Ajzen, I., 1991. The theory of planned behavior. *Organ. Behav. Hum. Decis. Process.* 50 (2), 179–211. [https://doi.org/10.1016/0749-5978\(91\)90020-T](https://doi.org/10.1016/0749-5978(91)90020-T).
- Albahli, S., Algham, A., Aeraj, S., Alsaeed, M., Alrashed, M., Tayyab Rauf, H., Arif, M., Abed Mohammed, M., 2021. COVID-19 public sentiment insights: a text mining approach to the Gulf countries. *Comput. Mater. Contin.* 67 (2), 1613–1627.
- Aycan, Z., 2006. Paternalism: towards conceptual refinement and operationalization. *Indigenous and Cultural Psychology: Understanding People in Context*.
- Bastian, M., Heymann, S., Jacomy, M., 2009. Gephi: An open source software for exploring and manipulating networks. In: Third Int. AAAI Conf. Weblogs Soc. Media. <https://doi.org/10.1136/qshc.2004.010033>.
- Calabrese, C., Anderton, B.N., Barnett, G.A., 2019. Online representations of “genome editing” uncover opportunities for encouraging engagement: a semantic network analysis. *Sci. Commun.* 41 (2), 222–242. <https://doi.org/10.1177/1075547018824709>.
- Calabrese, C., Ding, J., Millam, B., Barnett, G.A., 2020. The uproar over gene-edited babies: a semantic network analysis of CRISPR on Twitter. *Environ. Commun.* 14 (7), 954–970. <https://doi.org/10.1080/17524032.2019.1699135>.
- Chandrasekaran, R., Mehta, V., Valkunde, T., Moustakas, E., 2020. Topics, trends, and sentiments of tweets about the COVID-19 pandemic: temporal infoveillance study. *J. Med. Internet Res.* 22 (10), e22624 <https://doi.org/10.2196/22624>.

- Cowan, N., 2016. Working Memory Capacity. Routledge, New York.
- Danowski, J.A., 1993. Network analysis of message content. In: Richards, W.D., Barnett, G.A. (Eds.), Progress in Communication Sciences. Norwood, Albex, pp. 197–220.
- Deiner, M.S., Fathy, C., Kim, J., Niemeyer, K., Ramirez, D., Ackley, S.F., Liu, F., Lietman, T.M., Porco, T.C., 2019. Facebook and Twitter vaccine sentiment in response to measles outbreaks. *Health Inf. J.* 25 (3), 1116–1132. <https://doi.org/10.1177/1460458217740723>.
- Ding, H., Zhang, J., 2010. Social media and participatory risk communication during the H1N1 flu epidemic: a comparative study of the United States and China. *China Media Res.* 6.
- Doerfel, M.L., Barnett, G.A., 1999. A semantic network analysis of the International Communication Association. *Hum. Commun. Res.* 25 (4), 589–603. <https://doi.org/10.1111/j.1468-2958.1999.tb00463.x>.
- Dubé, E., Laberge, C., Guay, M., Bramadat, P., Roy, R., Bettinger, J.A., 2013. Vaccine hesitancy: an overview. *Hum. Vaccines Immunother.* 9 (8), 1763–1773. <https://doi.org/10.4161/hv.24657>.
- Dunn, A.G., Surian, D., Leask, J., Dey, A., Mandl, K.D., Coiera, E., 2017. Mapping information exposure on social media to explain differences in HPV vaccine coverage in the United States. *Vaccine* 35 (23), 3033–3040. <https://doi.org/10.1016/j.vaccine.2017.04.060>.
- Dutta, M.J., 2007. Communicating about culture and health: theorizing culture-centered and cultural sensitivity approaches. *Commun. Theory* 17 (3), 304–328. <https://doi.org/10.1111/comt.2007.17.issue-310.1111.j.1468-2885.2007.00297.x>.
- Featherstone, J.D., Barnett, G.A., Ruiz, J.B., Zhuang, Y., Millam, B.J., 2020a. Exploring childhood anti-vaccine and pro-vaccine communities on twitter – a perspective from influential users. *Online Soc. Networks Media* 20, 100105. <https://doi.org/10.1016/j.osnem.2020.100105>.
- Featherstone, J.D., Ruiz, J.B., Barnett, G.A., Millam, B.J., 2020b. Exploring childhood vaccination themes and public opinions on Twitter: a semantic network analysis. *Telemat. Inf.* 54, 101474. <https://doi.org/10.1016/j.tele.2020.101474>.
- fxsjy, n.d., jieba. Retrieved from <https://github.com/fxsjy/jieba>.
- Gao, R., Hao, B., Li, H., Gao, Y., Zhu, T., 2013. Developing simplified Chinese psychological linguistic analysis dictionary for microblog. In: Lecture Notes in Computer Science. https://doi.org/10.1007/978-3-319-02753-1_36.
- Gelfand, M.J., Erez, M., Aycan, Z., 2007. Cross-cultural organizational behavior. *Annu. Rev. Psychol.* 58 (1), 479–514. <https://doi.org/10.1146/annurev.psych.58.110405.085559>.
- Gever, V.C., Talabi, F.O., Adelabu, O., Sanusi, B.O., Talabi, J.M., 2021. Modeling predictors of COVID-19 health behaviour adoption, sustenance and discontinuation among social media users in Nigeria. *Telemat. Inf.* 60, 101584. <https://doi.org/10.1016/j.tele.2021.101584>.
- Graham, B.S., 2020. Rapid COVID-19 vaccine development. *Science* 368 (6494), 945–946. <https://doi.org/10.1126/scienceabb8923>.
- Grandey, A., Rafaeli, A., Ravid, S., Wirtz, J., Steiner, D.D., 2010. Emotion display rules at work in the global service economy: the special case of the customer. *J. Serv. Manag.* 21 (3), 388–412. <https://doi.org/10.1108/09564231011050805>.
- Guntuku, S.C., Buttenheim, A.M., Sherman, G., Merchant, R.M., 2021. Twitter discourse reveals geographical and temporal variation in concerns about COVID-19 vaccines in the United States. *Vaccine* 39 (30), 4034–4038. <https://doi.org/10.1016/j.vaccine.2021.06.014>.
- Habibabadi, S.K., Haghghi, P.D., 2019. Topic modelling for identification of vaccine reactions in Twitter. In: ACM International Conference Proceeding Series. <https://doi.org/10.1145/3290688.3290735>.
- Hanneman, R.A., Riddle, M., 2005. Introduction to social network methods. Riverside, CA Univ. California, Riverside. On-line Textb. 46. <https://doi.org/10.1016/j.socnet.2006.08.002>.
- Haque, A., Pant, A.B., 2020. Efforts at COVID-19 vaccine development: Challenges and successes. *Vaccines* 8 (4), 739. <https://doi.org/10.3390/vaccines8040739>.
- Henrich, N., Holmes, B., 2011. What the public was saying about the H1N1 vaccine: perceptions and issues discussed in on-line comments during the 2009 H1N1 pandemic. *PLoS One* 6 (4). <https://doi.org/10.1371/journal.pone.0018479>.
- Hilbert, M., Barnett, G., Blumenstock, J., Contractor, N., Diesner, J., Frey, S., et al., 2019. Computational communication science: a methodological catalyzer for a maturing discipline. *Int. J. Commun.* 13.
- Hofstede, G., 2011. Dimensionalizing cultures: the Hofstede model in context. *Online Readings Psychol. Cult.* 2 <https://doi.org/10.9707/2307-0919.1014>.
- Hofstede, G., Hofstede, G.J., 1993. Cultures and organizations - Software of the mind: intercultural cooperation and its importance for survival. *Admin. Sci. Q.*
- Hofstede Insights., n.d.. Country comparison between China and the United States. Retrieved from <https://www.hofstede-insights.com/country-comparison/china-the-usa/>.
- Hofstede Insights, 2021. Compare countries. Retrieved from <https://www.hofstede-insights.com/product/compare-countries/>.
- Hu, T., Wang, S., Luo, W., Yan, Y., Zhang, M., Huang, X., Liu, R., Ly, K., Kacker, V., Li, Z., 2021. Revealing public opinion towards COVID-19 vaccines using Twitter data in the United States a spatiotemporal perspective. medRxiv. <https://doi.org/10.1101/2021.06.02.21258233>.
- Huang, C., Xu, X., Cai, Y., Ge, Q., Zeng, G., Li, X., Zhang, W., Ji, C., Yang, L., 2020. Mining the characteristics of COVID-19 patients in china: analysis of social media posts. *J. Med. Internet Res.* 22 (5), e19087. <https://doi.org/10.2196/19087>.
- Jiang, K., Anderton, B.N., Ronald, P.C., Barnett, G.A., 2018. Semantic network analysis reveals opposing online representations of the search term “GMO”. *Glob. Challenges* 2 (1). <https://doi.org/10.1002/gch2.201700082>.
- Johnson, N.F., Velásquez, N., Restrepo, N.J., Leahy, R., Gabriel, N., El Oud, S., Zheng, M., Manrique, P., Wuchty, S., Lupu, Y., 2020. The online competition between pro- and anti-vaccination views. *Nature* 582 (7811), 230–233. <https://doi.org/10.1038/s41586-020-2281-1>.
- Kang, G.J., Ewing-Nelson, S.R., Mackey, L., Schlitt, J.T., Marathe, A., Abbas, K.M., Swarup, S., 2017. Semantic network analysis of vaccine sentiment in online social media. *Vaccine* 35 (29), 3621–3638. <https://doi.org/10.1016/j.vaccine.2017.05.052>.
- Kata, A., 2012. Anti-vaccine activists, Web 2.0, and the postmodern paradigm - an overview of tactics and tropes used online by the anti-vaccination movement. *Vaccine* 30 (25), 3778–3789. <https://doi.org/10.1016/j.vaccine.2011.11.112>.
- Kaur, S.P., Gupta, V., 2020. COVID-19 vaccine: a comprehensive status report. *Virus Res* 288, 198114. <https://doi.org/10.1016/j.virusres.2020.198114>.
- Kreuter, M.W., McClure, S.M., 2004. The role of culture in health communication. *Annu. Rev. Public Health* 25 (1), 439–455. <https://doi.org/10.1146/annurev.pubhealth.25.101802.123000>.
- Kwon, K., Barnett, G.A., Chen, H., 2009. Assessing cultural differences in translations: a semantic network analysis of the universal declaration of human rights. *J. Int. Intercult. Commun.* 2 (2), 107–138. <https://doi.org/10.1080/17513050902759488>.
- Lama, Y., Hu, D., Jamison, A., Quinn, S.C., Broniatowski, D.A., 2019. Characterizing trends in human papillomavirus vaccine discourse on Reddit (2007–2015): an observational study. *JMIR Public Heal. Surveill.* 5 (1), e12480. <https://doi.org/10.2196/12480>.
- Lazarus, J.V., Ratzan, S.C., Palayew, A., Gostin, L.O., Larson, H.J., Rabin, K., Kimball, S., El-Mohandes, A., 2021. A global survey of potential acceptance of a COVID-19 vaccine. *Nat. Med.* 27 (2), 225–228. <https://doi.org/10.1038/s41591-020-1124-9>.
- Lee, J., Kim, K., Park, G., Cha, N., 2021. The role of online news and social media in preventive action in times of infodemic from a social capital perspective: the case of the COVID-19 pandemic in South Korea. *Informatics* 64, 101691. <https://doi.org/10.1016/j.tele.2021.101691>.
- Li, Y., Luo, C., Chen, A., 2019. The evolution of online discussions about GMOs in China over the past decade: changes, causes and characteristics. *Cult. Sci.* 2 (4), 311–325. <https://doi.org/10.1177/209660831900200406>.
- Lu, J., Qiu, Y., 2013. Microblogging and social change in China. *Asian Perspect.* 37 (3), 305–331. <https://doi.org/10.1353/apr.2013.0012>.
- Lu, L., Liu, J., Yuan, Y.C., 2020. Health information seeking behaviors and source preferences between Chinese and U.S. populations. *J. Health Commun.* 25 (6), 490–500. <https://doi.org/10.1080/10810730.2020.1806414>.
- Lu, L., Liu, J., Yuan, Y.C., 2020. Cultural differences in cancer information acquisition: cancer risk perceptions, fatalistic beliefs, and worry as predictors of cancer information seeking and avoidance in the U.S. and China. *Health Commun.* 1–10. <https://doi.org/10.1080/10410236.2021.1901422>.
- Luo, C., Ji, K., Tang, Y., Du, Z., 2021. Exploring the expression differences between professionals and laypeople toward the COVID-19 vaccine: Text mining approach. *J. Med. Internet Res.* 23 (8), e30715 <https://doi.org/10.2196/30715>.
- Luo, C., Li, Y., Chen, A., Tang, Y., 2020. What triggers online help-seeking retransmission during the COVID-19 period? Empirical evidence from Chinese social media. *PLoS One.* 15 (11) <https://doi.org/10.1371/journal.pone.0241465>.

- Lyu, J.C., Han, E.L., Luli, G.K., 2021. COVID-19 vaccine-related discussion on Twitter: topic modeling and sentiment analysis. *J. Med. Internet Res.* 23 (6) <https://doi.org/10.2196/24435>.
- Maier, D., Waldherr, A., Miltner, P., Wiedemann, G., Niekler, A., Keinert, A., Pfetsch, B., Heyer, G., Reber, U., Häussler, T., Schmid-Petri, H., Adam, S., 2018. Applying LDA topic modeling in communication research: toward a valid and reliable methodology. *Commun. Methods Meas.* 12 (2-3), 93–118. <https://doi.org/10.1080/19312458.2018.1430754>.
- Malik, A.A., McFadden, S.M., Elharake, J., Omer, S.B., 2020. Determinants of COVID-19 vaccine acceptance in the US. *EClinicalMedicine*. 26, 100495. <https://doi.org/10.1016/j.eclinm.2020.100495>.
- Margolin, D., Liao, W., 2018. The emotional antecedents of solidarity in social media crowds. *New Media Soc.* 20 (10), 3700–3719. <https://doi.org/10.1177/1461444818758702>.
- Massey, P.M., Leader, A., Yom-Tov, E., Budenz, A., Fisher, K., Klassen, A.C., 2016. Applying multiple data collection tools to quantify human papillomavirus vaccine communication on twitter. *J. Med. Internet Res.* 18 (12), e318. <https://doi.org/10.2196/jmir.6670>.
- Miller, G.A., 1956. The magical number seven, plus or minus two: some limits on our capacity for processing information. *Psychol. Rev.* 63 (2), 81–97. <https://doi.org/10.1037/h0043158>.
- Moran, C.M., Dieffendorff, J.M., Greguras, G.J., 2013. Understanding emotional display rules at work and outside of work: the effects of country and gender. *Motiv. Emot.* 37 (2), 323–334. <https://doi.org/10.1007/s11031-012-9301-x>.
- Murphy, J., Vallières, F., Bentall, R.P., Shevlin, M., McBride, O., Hartman, T.K., McKay, R., Bennett, K., Mason, L., Gibson-Miller, J., Levita, L., Martinez, A.P., Stocks, T.V.A., Karatzias, T., Hyland, P., 2021. Psychological characteristics associated with COVID-19 vaccine hesitancy and resistance in Ireland and the United Kingdom. *Nat. Commun.* 12 (1) <https://doi.org/10.1038/s41467-020-20226-9>.
- Nan, X., Madden, K., 2012. HPV vaccine information in the blogosphere: How positive and negative blogs influence vaccine-related risk perceptions, attitudes, and behavioral intentions. *Health Commun.* 27 (8), 829–836. <https://doi.org/10.1080/10410236.2012.661348>.
- Our World in Data., n.d. Statistics and research: Coronavirus (COVID-19) vaccinations. Retrieved from <https://ourworldindata.org/covid-vaccinations?country=CHN~USA>.
- Pan, S., Zhang, D., Zhang, J., 2020a. Caught in the crossfire: how contradictory information and norms on social media influence young women's intentions to receive HPV vaccination in the United States and China. *Front. Psychol.* 11 <https://doi.org/10.3389/fpsyg.2020.548365>.
- Pan, W., Feng, B., Shen, C., 2020b. Examining social capital, social support, and language use in an online depression forum: Social network and content analysis. *J. Med. Internet Res.* 22 (6), e17365. <https://doi.org/10.2196/17365>.
- Pasick, R.J., D'Onofrio, C.N., Otero-Sabogal, R., 1996. Similarities and differences across cultures: questions to inform a third generation for health promotion research. *Heal. Educ. Behav.* 23 <https://doi.org/10.1177/019584029602300610>.
- Perea, A., Slater, M.D., 1999. Power distance and collectivist/individualist strategies in alcohol warnings: effects by gender and ethnicity. *J. Health Commun.* 4 <https://doi.org/10.1080/108107399126832>.
- Radzikowski, J., Stefanidis, A., Jacobsen, K.H., Croitoru, A., Crooks, A., Delamater, P.L., 2016. The measles vaccination narrative in twitter: a quantitative analysis. *JMIR Publ. Heal. Surveill.* 2 (1), e1. <https://doi.org/10.2196/publichealth.5059>.
- Rains, S.A., 2020. Big data, computational social science, and health communication: a review and agenda for advancing theory. *Health Commun.* 35 (1), 26–34. <https://doi.org/10.1080/10410236.2018.1536955>.
- Ruiz, J.B., Barnett, G.A., 2015. Exploring the presentation of HPV information online: a semantic network analysis of websites. *Vaccine* 33 (29), 3354–3359. <https://doi.org/10.1016/j.vaccine.2015.05.017>.
- Ruiz, J.B., Bell, R.A., 2021. Predictors of intention to vaccinate against COVID-19: Results of a nationwide survey. *Vaccine* 39 (7), 1080–1086. <https://doi.org/10.1016/j.vaccine.2021.01.010>.
- Saha, K., Torous, J., Caine, E.D., De Choudhury, M., 2020. Psychosocial effects of the COVID-19 pandemic: large-scale quasi-experimental study on social media. *J. Med. Internet Res.* 22 (11), e22600. <https://doi.org/10.2196/22600>.
- Saleh, S.N., McDonald, S.A., Basit, M.A., Kumar, S., Arasaratnam, R.J., Perl, T.M., Lehmann, C.U., Medford, R.J., 2021. Public perception of COVID-19 vaccines through analysis of Twitter content and users. *medRxiv*. <https://doi.org/10.1101/2021.04.19.21255701>.
- Samuel, J., Ali, G.G.M.N., Rahman, M.M., Esawi, E., Samuel, Y., 2020. COVID-19 public sentiment insights and machine learning for tweets classification. *Informatics* 11 (6), 314. <https://doi.org/10.3390/info11060314>.
- Shen, C., Chen, A., Luo, C., Zhang, J., Feng, B., Liao, W., 2020. Using reports of symptoms and diagnoses on social media to predict COVID-19 case counts in mainland china: Observational infoveillance study. *J. Med. Internet Res.* 22 (5), e19421. <https://doi.org/10.2196/19421>.
- Shoup, J.A., Narwaney, K.J., Wagner, N.M., Kraus, C.R., Gleason, K.S., Albright, K., Glanz, J.M., 2019. Social media vaccine websites: a comparative analysis of public and moderated websites. *Heal. Educ. Behav.* 46 (3), 454–462. <https://doi.org/10.1177/1090198118818253>.
- Siemaszko, C., 2021. Experts praise Biden's COVID-19 plan, but warn that undoing Trump-era mistakes will take time. NBC News. Retrieved from <https://www.nbcnews.com/news/us-news/experts-praise-biden-s-covid-19-plan-warn-undoing-trump-n1255210>.
- Skeppstedt, M., Kerren, A., Stede, M., 2018. Vaccine hesitancy in discussion forums: computer-assisted argument mining with topic models. In: *Studies in Health Technology and Informatics*. <https://doi.org/10.3233/978-1-61499-852-5-366>.
- Smith, R.A., Parrott, R.L., 2012. Mental representations of HPV in Appalachia: Gender, semantic network analysis, and knowledge gaps. *J. Health Psychol.* 17 (6), 917–928. <https://doi.org/10.1177/1359105311428534>.
- SocialSensor, n.d.. More social insights use SocialSenor. Retrieved from <http://socialsensor.top/>.
- Song, Y., Kwon, K.H., Lu, Y., Fan, Y., Li, B., 2021. The "parallel pandemic" in the context of China: the spread of rumors and rumor-corrections during COVID-19 in Chinese social media. *Am. Behav. Sci.* <https://doi.org/10.1177/00027642211003153>.
- spaCy, n.d.. spaCy: Industrial-strength natural language processing. Retrieved from <https://spacy.io/>.
- Su, Y., Xue, J., Liu, X., Wu, P., Chen, J., Chen, C., Liu, T., Gong, W., Zhu, T., 2020. Examining the impact of covid-19 lockdown in Wuhan and Lombardy: a psycholinguistic analysis on Weibo and Twitter. *Int. J. Environ. Res. Publ. Health* 17 (12), 4552. <https://doi.org/10.3390/ijerph17124552>.
- Sun, W., Yu, J., Yang, W., Yan, X., Qiang, L., Xia, K., 2021. China vaccinating key groups against COVID-19. *Xinhua Net*. Retrieved from http://www.xinhuanet.com/english/2021-01/04/c_139641409.htm.
- Tan, Y., 2021. COVID: What do we know about China's coronavirus vaccines? BBC News. Retrieved from <https://www.bbc.com/news/world-asia-china-55212787>.
- Tang, L., Peng, W., 2015. Culture and health reporting: a comparative content analysis of newspapers in the United States and China. *J. Health Commun.* 20 (2), 187–195. <https://doi.org/10.1080/10810730.2014.920060>.
- Tanne, J.H., 2020. Covid-19: US needs a national plan to fight rising infections, experts say. *BMJ* 370. <https://doi.org/10.1136/bmj.m3072>.
- Tausczik, Y.R., Pennebaker, J.W., 2010. The psychological meaning of words: LIWC and computerized text analysis methods. *J. Lang. Soc. Psychol.* 29 (1), 24–54. <https://doi.org/10.1177/0261927X09351676>.
- Triandis, H.C., 2001. Individualism-collectivism and personality. *J. Pers.* 69 (6), 907–924. <https://doi.org/10.1111/1467-6494.696169>.
- twintproject, n.d.. Twint: Twitter intelligence tool. Retrieved from <https://github.com/twintproject/twint>.
- van Atteveldt, W., Peng, T.-Q., 2018. When communication meets computation: opportunities, challenges, and pitfalls in computational communication science. *Commun. Methods Meas.* 12 (2-3), 81–92. <https://doi.org/10.1080/19312458.2018.1458084>.
- World Health Organization, n.d.. Coronavirus disease (COVID-19): COVID-19 vaccines. Retrieved from <https://www.who.int/emergencies/diseases/novel-coronavirus-2019/covid-19-vaccines>.
- World Health Organization., 2021. Coronavirus disease (COVID-19) pandemic: Numbers at a glance. Retrieved from <https://www.who.int/emergencies/diseases/novel-coronavirus-2019>.
- Xu, B., 2014. Media censorship in China. CFR.Org.

- Xu, Z., 2019. Personal stories matter: topic evolution and popularity among pro- and anti-vaccine online articles. *J. Comput. Soc. Sci.* 2 (2), 207–220. <https://doi.org/10.1007/s42001-019-00044-w>.
- Xu, Z., Guo, H., 2018. Using text mining to compare online pro- and anti-vaccine headlines: word usage, sentiments, and online popularity. *Commun. Stud.* 69 (1), 103–122. <https://doi.org/10.1080/10510974.2017.1414068>.
- Zhang, J., Featherstone, J.D., Calabrese, C., Wojcieszak, M., 2021. Effects of fact-checking social media vaccine misinformation on attitudes toward vaccines. *Prev. Med.* 145, 106408. <https://doi.org/10.1016/j.ypmed.2020.106408>.