Diffusion of vaccine misinformation in a Taiwanese online community: The role of influencers and echo chambers

Jason Dean-Chen Yin, Tzu-Chin Wu, Chia-Yun Chen, Xiaohui Wang

Submitted to: Journal of Medical Internet Research
on: March 01, 2024

Table of Contents

Diffusion of vaccine misinformation in a Taiwanese online community: The role of influencers and echo chambers

Jason Dean-Chen Yin[1]; Tzu-Chin Wu[2]; Chia-Yun Chen[2]; Xiaohui Wang[3] PhD

[1]School of Public Health, University of Hong Kong Hong Kong HK
[2]College of Public Health, National Taiwan University Taiwan TW
[3]Health and Biomedical Sciences RMIT University Melbourne AU

Corresponding Author:
Xiaohui Wang PhD
Health and Biomedical Sciences
RMIT University
124 La Trobe Street
Melbourne
AU

Abstract

Background: Prevalence of and spread of misinformation are a concern for the exacerbation of vaccine hesitancy and a resulting reduction in vaccine intent. However, few studies have focused on how vaccine misinformation diffuses online, who is responsible for the diffusion, and the mechanisms by which that happens. In addition, researchers have rarely investigated this in non-western contexts particularly vulnerable to misinformation.

Objective: This study aims to identify COVID-19 vaccine misinformation, assess its diffusion, and identify the key users responsible for its transmission on a Taiwanese online forum.

Methods: The study uses data from a popular forum in Taiwan, PTT. A crawler scraped all threads on the most popular subforum from January 2021 until December 2022. After, the Chinese word for “vaccine” filtered the corpus for any threads mentioning vaccines (n=5,818). Labels of misinformation types derived from the literature were assigned by two raters, which were further collapsed into “true information” and “false information”. Diffusion breadth was assessed with a regression model. Polarity was proposed as a proxy for measuring echo chambering, the mechanism for spreading misinformation; the association of node-level properties to polarity identified key users spreading misinformation.

Results: Misinformation content did not vary much from other contexts. For diffusion breadth, propaganda was most likely to be reposted (IRR: 2.07, P<.001) relative to true information. However, the more polar the user’s commenting behaviour, the less likely to be reposted (IRR: 0.22, P<.001), suggesting a lack of echo chambering. Nevertheless, users that were high commenters and “brokers” drove polarity and echo chambering.

Conclusions: While the forum exhibits a resilience to echo chambering, active users and brokers contribute significantly to the polarization of the community, particularly through propaganda-style misinformation. More effort can be put into moderating these users to prevent polarisation and spread of misinformation to prevent growing vaccine hesitancy.

(JMIR Preprints 01/03/2024:57951)
DOI: https://doi.org/10.2196/preprints.57951

Yes, but please make my accepted manuscript PDF available only to logged-in users; I understand that the title and abstract will remain v
Yes, but only make the title and abstract visible (see Important note, above). I understand that if I later pay to participate in <a href="http

Original Manuscript

Diffusion of vaccine misinformation in a Taiwanese online community: The role of influencers and echo chambers

Abstract

Background: Prevalence of and spread of misinformation are a concern for the exacerbation of vaccine hesitancy and a resulting reduction in vaccine intent. However, few studies have focused on how vaccine misinformation diffuses online, who is responsible for the diffusion, and the mechanisms by which that happens. In addition, researchers have rarely investigated this in non-western contexts particularly vulnerable to misinformation.

Objective: This study aims to identify COVID-19 vaccine misinformation, assess its diffusion, and identify the key users responsible for its transmission on a Taiwanese online forum.

Methods: The study uses data from a popular forum in Taiwan, PTT. A crawler scraped all threads on the most popular subforum from January 2021 until December 2022. After, the Chinese word for "vaccine" filtered the corpus for any threads mentioning vaccines (n=5,818). Labels of misinformation types derived from the literature were assigned by two raters, which were further collapsed into "true information" and "false information". Diffusion breadth was assessed with a regression model. Polarity was proposed as a proxy for measuring echo chambering, the mechanism for spreading misinformation; the association of node-level properties to polarity identified key users spreading misinformation.

Results: Misinformation content did not vary much from other contexts. For diffusion breadth, propaganda was most likely to be reposted (IRR: 2.07, $P<.001$) relative to true information. However, the more polar the user's commenting behaviour, the less likely to be reposted (IRR: 0.22, $P<.001$), suggesting a lack of echo chambering. Nevertheless, users that were high commenters and "brokers" drove polarity and echo chambering.

Conclusions: While the forum exhibits a resilience to echo chambering, active users and brokers contribute significantly to the polarization of the community, particularly through propaganda-style misinformation. More effort can be put into moderating these users to prevent polarisation and spread of misinformation to prevent growing vaccine hesitancy.

Introduction

As individuals increasingly turn to social media as a primary source of information, the prevalence and spread of unverified or misinformed scientific claims is concerning (Bessi et al., 2015). Social media users gravitate toward information that validates their belief systems, forming echo chambers that validate their shared narrative (Colleoni et al., 2014). These echo chambers can be the launching pads for misinformation that goes viral (Bessi et al., 2014). Worse, they can influence opinions on issues of public concern, such as vaccination (Schmidt et al., 2018).

As early as 2001, studies have identified the rise of vaccine hesitancy online (Davies et al., 2002; R. K. Zimmerman et al., 2005) and catalogued the techniques in anti-vaccination misinformation transmission (Friedlander, 2001; Kata, 2010). These studies paralleled the early days of the World Wide Web and focus solely on analysing web pages. An early study by Zimmerman found that misrepresentation (twisting of content) was a method in conveying vaccine misinformation (R. K. Zimmerman et al., 2005). Kata elaborates on misrepresentation in her study in 2010 on childhood vaccination. In her study, misinformation, a sort of misrepresentation, was a main anti-vaccination theme that arose in classification. Under the misinformation umbrella, she found that using outdated sources; misrepresenting facts; self-referencing to "experts"; no referencing to statistics or citations; and making unsupported statements were all ways of passing misinformation (Kata, 2010). The use of negative tones is also a method of strengthening anti-vaccination methods (Donzelli et al., 2018).

As misinformation became more prevalent through social media, exacerbated no less by the terming of "fake news" and a global pandemic, more work on clarifying the definition of misinformation, and classifying the different kinds of misinformation occurred.

The current consensus is that misinformation is defined as false or inaccurate information, whereas disinformation is deliberate produced to harm people, organisations, or countries. Under these umbrellas, there are different types of mis- and disinformation. Some information can be fabricated content, some can be manipulated to be click-bait. Some can be satires or parody passing off as true, and some can be propaganda. Information can be passed off as true via sponsors and be partially true or totally false. New modes of producing synthetic media through artificial intelligence such as "Deep Fake" distort reality by passing as true. While there is nuance between the different types of mis- and disinformation, all types are distinct from true information, which is neither deliberately fabricated with malintent nor containing false (scientific) information.

There are several studies on classifying types of vaccine misinformation. Zimmermann *et al.*, in their study on COVID-19, found that misinformation fell into six categories: 1) medical misinformation, concerning deaths, acquired immunity, and "not needing" the vaccine; scientific misinformation, concerning doubts on vaccine development, ingredients, and testing; political misinformation, concerning suspicions on government, politicians, Dr. Anthony Fauci (head of science); media misinformation, concerning the twisting of truth, propaganda; religious misinformation, concerning comments related to the bible, and attribution of the vaccine as the "mark of the beast"; and technological misinformation, concerning microchipping (T. Zimmerman et al., 2023). Zhao *et al.*'s study does not deviate far from this. They identified that misinformation could capture conspiracies; concerns on vaccine safety and efficacy; a flat rejection for all vaccines; morality (including religion and human experimenting); and a violation of civil liberties (Zhao et al., 2023). Classification studies also identified new modes of transmission. Basch *et al.* studied the types of misinformation on TikTok, a medium mixing audio-visual and textual cues, and found that parodying or the overemphasis on false consequences of available vaccines were all methods of strengthening an anti-vaccination narrative (Corey H. Basch et al., 2021).

In addition to modes of transmission and classification, some studies have focused on linking misinformation to vaccination intent, although sparse. One study used a questionnaire to identify that COVID-19 vaccine hesitancy mediated the relationship between vaccine knowledge and vaccination intention, with misinformation on vaccines associating with higher vaccine hesitancy. The same study also claims that most respondents were exposed to COVID-19 misinformation (Lee et al., 2022). Another study conducted a randomised controlled trial, finding that exposure to recent misinformation induced a decline in intent of vaccination. This is especially true when the misinformation is transmitted as misrepresenting facts of a scientific nature (Loomba et al., 2021).

In the studies on vaccine misinformation, there are unexplored avenues. Few studies have examined how vaccine misinformation diffuses online, both in time and in quantity. Diffusion is a communication process whereby information is communicated over time "among the members of a social system" (Rogers, 1995). Often, this process is measured in terms of depth, breadth and speed (Van den Bulte, 2000; Yang & Counts, 2010). Diffusion breadth refers to the length of the longest transmission chain, breadth refers to the capacity to generate offspring posts, and diffusion speed refers to the efficiency of the information diffusion process (Zhang & Peng, 2015). Understanding the diffusion process between true and misinformation is important because, should approaches such as psychological inoculation (van der Linden et al., 2021) or other vaccination community strategies work (Shelby & Ernst, 2013; Whitehead et al., 2023), understanding the scale of spread and when to intervene diminishes the spread.

In addition, no studies have studied key users' roles in spreading vaccine misinformation. Previous research found that echo chambers are related to misinformation diffusion (Törnberg, 2018). Misinformation disseminated by echo chambers spread more virally than those not distributed by them (Choi et al., 2020). However, a critical factor in echo chambering is not the mere clustering, but the deliberate exclusion of dissimilar perspectives (Bruns, 2017). Indeed, social media, given its prevalence of weak ties (Granovetter, 1973), is also likely to inadvertently expose users to a diversity of information and opinions, breaking the echo chamber (De Meo et al., 2013; Weng et al., 2013). This is particularly problematic when the users doing the exclusion are both lay persons (Kim & Valente, 2020) and central in the network. Two studies found that information diffused by "brokers" – those who have high betweenness centrality – affects the final size of information cascades (Bakshy et al., 2012; Weng et al., 2013). For health information, diffusion size of posts by the U.S. Centers for Disease Control and Prevention were related to broker involvement (Meng et al., 2018). More work can thus be done on understanding how key users aid in spreading vaccine misinformation through deliberate exclusion of "true news", thereby enhancing its dissemination.

The consequence of having these key users spread information lies in the fact that individual beliefs are shaped by their immediate social network, both online and offline (DiFonzo et al., 2014). These worlds feedback to each other, entrenching belief. Scholars have found that dissemination of misinformation is driven by social reinforcement in an individual's digital circles (De Domenico et al., 2013). If a person's network consists of mostly rumourmongers, that person in turn likely propagates the same misinformation. This propagation often spills into the offline space, influencing judgement through reinforcing the legitimacy of the information online (Difonzo, 2018), eventually creating fissures along sociodemographic lines, further polarising the offline world (Fine, 2007). Should this process occur for vaccine information, it would exacerbate the issue of vaccine hesitancy, and have negative implications for vaccination. Few studies have examined the upstream part of this process, and no less in non-western contexts (Fine, 2007). This study focuses on vaccine misinformation on a local forum in Taiwan from three aspects: identifying the types of misinformation, describing how it diffuses relative to regular news, and assessing how influential users fall into chambers of misinformation, affecting its spread.

1 Research questions

The current study uses the same PTT data to address the following questions on misinformation. First, what are the types of misinformation in a Taiwanese online community? This identification and categorisation archives how misinformation topics differ to other contexts considering the socio-political context of Taiwan. Second, the study describes at how misinformation cascades differ between true and false information by dichotomising the topics, comparing their breadth (Zhang & Peng, 2015). Finally, I assess to what extent the echo chamber phenomenon exists in the diffusion of misinformation and how influential users, as a proxy for understanding key spreaders of misinformation, affect the echo chamber in the network. The findings of this study can inform how Taiwan can combat growing misinformation in its diverse online ecology.

Methods

1 Data procurement

PTT is a terminal-based bulletin board system developed in Taiwan in 1995. Functioning like an internet forum, PTT is often termed Taiwan's "Reddit" and is one of the most active forums in Taiwan. From July 2022 to July 2023, the average users per day was 56,000 (PTT, 2023). The web-based version of PTT is structured into different *boards*, which are equivalent to thematic groups, on a forum. Within each board, there are threads or topics started. On each thread, the poster's metadata such as the username, time of post, and IP address are available for scraping. Also within threads is the comment section for which the corresponding metadata is also available.

The current study focuses on Taiwan's spread of COVID-19 vaccine misinformation from January 2021 until December 2022. Using a crawler, I scraped all threads on the "Gossiping" board – an all-purpose, miscellaneous topic board and the one most frequently browsed. After, I used the Chinese language word for "vaccine" to filter the corpus for any threads mentioning vaccines. In total, 5,818 boards were pulled.

2 Identifying misinformation

To identify misinformation, I first consolidated a broad classification scheme presented in Table 1. These broad categories are distilled from earlier studies that classified the different types of misinformation in the social media era. Using this schema, I educated two coders about the potential types of misinformation they would come across. The coders classified a random selection of 500 forum posts on vaccine-related PTT boards into the classification schema, with an aim for Cohen's Kappa > 0.90.

Table 1. Labelling scheme for true information and false information

Label		**Classification criteria**
Factual information (descriptive)	True information	Reporting of news events or facts without interpretation or analysis
Scientifically accurate analytical content		Interpreting or analysis of facts or data to provide deeper understanding
Misinformation	False information	False or inaccurate information, regardless of intention
Disinformation		Deliberately created and shared with the intent to mislead or deceive
Propaganda		Biased or misleading information used to

		promote political cause or push point of view
Fabricated content		Entirely false content designed to deceive and mislead (create fake news source, fake quotes, non-existent events)
Conspiracy		Belief or explanation that something is a result of a secret plot by a group or organisation
Two or more		Any two combinations of the false news categories.
Religious beliefs	N/A	Any discussion of religion in relation to vaccination
Unrelated	N/A	Boards containing “vaccine” keyword but unrelated to vaccine information or misinformation

Any disagreements among coders were resolved through discussion amongst themselves. As a standard reference, I consolidated a library of misinformation on COVID-19 vaccines in Taiwan from three fact-checking organisations from Taiwan: MyGoPen (MGP Fact Check Ltd., 2023), Cofacts (g0v, 2023), and Taiwan FactCheck Center (Taiwan FactCheck Foundation, 2023). These organisations, led by civil society movements combatting misinformation, consolidated potentially misinformative news on a variety of topics, including those related to COVID-19. COVID-19 vaccine-related boards were filtered through using “vaccine” as a keyword in Chinese. In the event of disagreements on classification, the COVID-19 vaccine-related misinformation on these sites were used as a final check. Following the initial calibration, the remaining 5,318 boards were split into two datasets (n=2,659) and independently coded. For comparing diffusion of misinformation and users’ polarized engagement with misinformation, the categories in Table 1 are further collapsed into “true” and “false” information. In addition, since many users on the forum post only once or twice, I distil a “core network” by extracting users with over 5 posts.

3 Diffusion of misinformation

The diffusion of information is traditionally measured in three ways: breadth, depth, and speed. These three aspects follow previously defined measurements on diffusion on social media platforms (Yang & Counts, 2010). However, given the structure of the PTT forum, depth is unascertainable. The reason for this is because in PTT, replies of replied posts always refer to the original post, and not the replied post. This metadata obscures the length of the diffusion chain. Compare this to platforms like X (previously Twitter) that link the diffusion chain through explicitly stating a “retweet” of a “retweet” is “retweeted” from the “retweet”, and not the original tweet. Due to the structure in PTT, breadth will be used to capture both concepts of breadth and depth for this study and will be used to proxy the two. In addition, “speed” for a traditional forum may not be considered useful due to its slower dissemination compared to other social media platforms. Thus, only breadth is used.

Breadth is the number of first-degree child nodes that repost it. If we denote a message as m and the set of first degree child nodes as $N(m)$, the breadth $B(m)$ is equivalent to $¿N(m)\vee¿$. Depth is the maximum length of the diffusion chain. For the same message m, the diffusion chain at each step i is represented as c_i, such that the maximum of this, $max\,(c_i)$ measures the depth, $D(m)$, of the message.

In addition, a negative binomial regression model will estimate the predictors of breadth. A negative binomial regression is used since overdispersion is expected for both breadth. To build the model, the categorical misinformation types will be input as a categorical variable, with "true information" as the baseline. In addition, three control variables will be used. First is the word count of the post. Previous research has suggested that longer posts have a higher likelihood to be transmitted (Berger & Milkman, 2012). Second is the activeness of the user, as operationalised by their previous posting history. While activity on a media platform does not necessarily mean higher engagement (Suh et al., 2010), it is an important confounding factor to include into the model. Third, the polarity score generated in the next section will be used. Polarity is included because it is possible that users who tend to be extreme on either spectrum are likely to have more engagement in the network. The regression model estimate is:

$$\log\,(\mu_i)=\beta_0+\beta_1(Misinformation)+\beta_2(Disinformation)+\beta_3(Propaganda)+\beta_4(Fabricated)+\beta_5(Propaganda)+\beta_6$$

where μ_i is the count of the dependent variable for the i^{th} observation of breadth of misinformation spread. The log link function relates the mean of the response variable to the linear predictors.

4 Measuring polarity (echo chamber)

Polarization in public opinion refers to the extent to which the views of a population (in this case, support for true or false information) is extreme and distinctly divided (Del Vicario et al., 2016). Polarization can be measure at the individual level or aggregated at the community level in which we used to identify the level of echo chamber. To measure individuals' level of polarity, we proposed two metrics for analysis.

The first is polarity measured by the difference in proportion of comments on true information and misinformation ("proportion polarity"). To measure this, I collect the commenting behaviour for each node v in the network. With their commenting history, $C(v)$, I calculate the number of comments on true and false information, denoted as $C_{pos}(v)$ and $C_{\neg¿(v)¿}$, respectively. The proportions of positive and negative comments are then $P_{pos(v)}=\frac{C_{pos}(v)}{C(v)}$ and $P_{\neg¿(v)=\frac{C_{\neg¿(v)}}{C(v)}¿¿}$, respectively. I subtract the proportion of negative comments from the proportion of positive comments to get the polarity score, $\pi_{¿}(v)$, per node using the equation $\pi_{¿}(v)=P_{pos}(v)-P_{\neg¿(v)¿}$. The range of $\pi_{¿}(v)$ is $-1\leq\pi_{¿}(v)\leq 1$, with a score of -1 representing a polarity in commenting only on false information; 0 representing an equal commenting on both, and 1 representing entirely commenting on true information.

The second is polarity measured by the absolute value of the difference in volume of comments on true and false information ("volume polarity"). Measuring by absolute value of the difference removes the true-false dichotomy and allows a straightforward interpretation of any polarity in the network, permitting a clearer interpretation of echo chambering. To calculate volume polarity, $\pi_{vol}(v)$, I take the absolute value of the difference of the number of negative to positive comments, $¿C_{\neg¿(v)-C_{pos}(v)\vee¿¿}$. The range of $\pi_{vol}(v)$ is then $0\leq\pi_{vol}(v)<inf$, with higher values indicating higher polarity. Figure 1 illustrates the distribution in polarity scores calculated by proportion (left) and volume (right) for the core network. For ease of interpretation in the negative binomial regression,

volume polarity value is min-max normalised to create a value between 0 and 1 due to the heaver left skew.

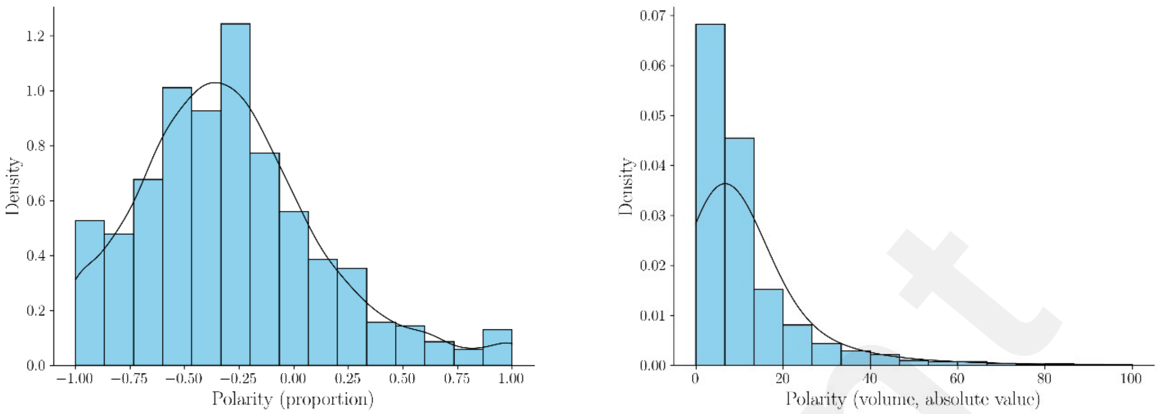

Figure 1. Distribution of polarity scores (n=2,422)

5 Node-level predictors of polarity

Influential users generally have disproportionate impact on the flow of network information, also shown in the previous chapter. Identifying them and their relation to polarity in the network thus is an important step in diminishing the spread of misinformation. Measures of centrality are usually used to identify node importance in the network. I use two centrality metrics to identify influential nodes, with each representing a different concept of influence.

The first measure of centrality is degree centrality, which directly measures the number of connections a node has. The more connections a node has, the more central and influential it is within the network. In PTT, since forum data is directional, the indegree and outdegree of a node will be calculated for each node separately. Decomposing degrees into indegrees and outdegrees helps distinguish whether nodes on either polar end are more an authority (indegree) or a broadcaster (outdegree) of misinformation.

The second measure of centrality is betweenness centrality, which measure the extent to which a node lies on paths between other nodes; specifically, capturing the frequency which a node appears on the shortest paths between pairs of nodes. Nodes with high betweenness centrality have control over information flow in the network, acting as “bridges” or “brokers” across the network (Everett & Valente, 2016). These nodes are critical for flow of information in the network because they function as “switches” for facilitating or inhibiting information flow. For the network, let σ_{st} denote the total number of shortest paths from node s to node t, and $\sigma_{st}(v)$ denote the number of those paths that pass through a node v. The betweenness centrality $b(v)$ can be defined as:

$$\sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

which sums over all pairs of nodes (s,t) in the network, excluding those which the pair is v, and for each pair, calculates the fraction of shortest paths between s and t that pass through v. Said another way, it calculates the proportion of times v is a bridge along the shortest path between two other nodes.

To analyse how polarity in the network changes in response to these nodes, two things are done. First, I isolate users that are more actively participating to obtain a “core network” to reduce the noise of single-time commenters. The threshold I use is a lifetime of n > 5 posts in the corpus. Then, I remove a subset of the percentage of top influential users – by increasing increments of 5% – and calculate and plot the average absolute value polarity score in the network. The resulting graphs of changing polarity indicate the change in overall posting behaviour on either true or misinformative threads by influential users.

Results

1 Identified misinformation

The results in Table 2 show the number of boards by each misinformation type in Table 1, in addition to an elaboration of several of the most common thread types. Out of a total n=5,818 threads, most threads (n=2,227, 38.3%) involve netizens asking questions for further clarification on vaccines. The next most common was reporting of official news reports or press conference news (n=1,603, 27.8%). For all threads containing misinformation, the most common was the “propaganda” type (n=858, 14.7%), indicating the relatively political nature of this forum. After disregarding the unrelated and religious threads, n=3,830 true threads and n=1,601 threads contained misinformation, for a total of n=5,431 boards for analysis moving forward.

Table 2. Counts and examples of common misinformation types in PTT

Label	n	Common types found	Example
Factual information (descriptive)	1,603	Official reports of vaccine side effects from government sites, often containing a “News” tag, with text fully reported. Most report official announcements or press conference news with no expression of opinion.	Title: “[News] Free registration now open! Vaccination booth stationed at the PX Mart near Christmas Land”
Scientifically accurate analytical content	2,227	Non-biased question-asking by “villagers”* that do not carry any slant in content, or a tone that instigates comments.	“Recently, there was a debate on vaccination, which we only heard the opposite side to not vaccinate. Yes, there are always safety concerns for any medical technology, and it is not 100% preventive of reinfection, but are there other reasons?”
Misinformation	452	Appears as a question (or comment) but has negative intentions of misleading the public (without understanding the origin of intention).	“We are now allowing children to get Moderna vaccines, but the side effects are large. According to Murphy’s Law, even if the probability is low, it is still possible. If a child does die after vaccination, who is responsible? … looking at a

			dazzling object, it's just tin foil. Behind cute makeup is just powder; even polished nails have dark edges."
Disinformation	97	Linking the vaccine as direct cause of other diseases or ailments (death, cyborgism, myocarditis, balding, *etc.*), and deriving these conclusions from personal experience.	"A lot of people are experiencing side effects from the vaccine, and if something happens, no one takes responsibility. Young people do not need vaccination since their ability to recover is incredibly strong, right? QQ"
Propaganda	858	Linking the reasons for vaccination to specific political attitudes. Often have the characteristic of replying to news posts, guided by personal opinions to specific political positions.	"The 'Taliban' really is ahead internationally, even half of their supporters refuse to roll up their sleeves for Medigen [Taiwan's domestic vaccine]. But maybe they can use it for a bath? The party can enjoy a good bath in their benevolent fluid" ["Taliban" is a derogatory internet slang term to refer to the Democratic Progressive Party, or "green" party in Taiwan. The Mandarin Chinese term substitutes the "li" in "Taliban" for the homophonic sound for "green"]
Fabricated content	195	Making non-factual statements, or describing stories related to vaccines based on unwarranted assumptions. Often begins with statements such as "I dreamed that…" or "My friend did …". Difficult to verify level of fabrication on text.	"Recently, a female college went to her OBGYN after her Moderna injection. She said her menstruation came twice a month. Some people also said after BNT, the heart was uncomfortable, and took a few days to pass. Why are there still people taking the third dose of MRNA? What's the gossip?"
Conspiracy	179	Linking vaccine administration or distribution with the hidden interests of the government and pharmaceutical companies. Mostly done along the lines of them achieving the "benefits" of controlling people if they control vaccine distribution.	"The original vaccines are developed using the original virus, but the virus is constantly mutating. Vaccine factories are not quick to develop new ones, and just encourage us to take booster doses. Isn't this just being done to cheat us of our money? Just like Intel, slowly squeezing out toothpaste, then launching the next generation of products when they can no longer make money."
Two or more misinformation types	29	Most cases of two or more involved some analytical component, used in a propaganda way.	–
Religious beliefs	23	After raising vaccine-related views, adding religious slogans or arguments. In some texts,	"I believe duolon [username] now. He said that vaccines are all planned to change human beings. Viruses are

		elaborated arguments include the viewpoints of a “false world” or “unknown forces”. Could also be categorised as broadly conspiracy, with religious grounding.	man-made and everything is planned. He said the heart used to be on the left side of the body, and now it’s in the center according to Google. I’m convinced. I do not want the vaccine. Do you believe duolon?”
Unrelated	155	–	–

*Villagers is a common term used on PTT that roughly translates to netizens.

Based on the examples for each category, there are no new types of misinformation narratives that appear in Taiwan. In fact, there are many reappearing narratives that mirror that of the west. One example is the conspiracy theory that vaccination is used as a means of control by governments or corporations (Jiang et al., 2021; Wawrzuta et al., 2021). Broadly speaking, these are symptoms of an overarching lack of trust in authorities on health, and part of the larger trend of anti-science (Baines et al., 2021; Lahouati et al., 2020; Okuhara et al., 2019; Tustin et al., 2018; Wawrzuta et al., 2021). This point is potentially exacerbated in geopolitically tense contexts such as Taiwan. One such example was the many narratives of faulty quality control prevalent for the Pfizer BioNTech vaccine, since its distributor for Greater China, Fosun, was Shanghai-based, and vaccines were refused as a result. The frequent appearance of linking (or discussing) vaccine decisions to political parties also corroborates this point; a trend also found in the United States (the United States and Taiwan share similar forms of government systems, as well as bipartisan polarization).

2 Diffusion of misinformation

For breadth, among threads identified containing true information, a total of 608 (15.9%) were shared at least once. Conversely, 165 (10.3%) of misinformative threads were reposted. Despite the difference in repost counts, the tendency of reposts for both types of threads was identical, with a median value of one repost. The most widely shared true thread had 35 reposts, while the most extensively circulated misinformation thread had 26 reposts. Comparing the average repost counts across the two groups, the data had no significant difference, with means of 2.39 and 2.33 reposts for true information and misinformation, respectively (t=0.250, P=.803). The 95% confidence interval for the two values ranged from -2.2 to 29.1 for true information threads and -1.1 to 10.3 for misinformation threads.

When looking at predictors of breadth in Table 3, there are several trends for breadth. For breadth, the regression revealed that the rate of repost for propaganda is double that of true information (2.07, p<0.005). However, for general disinformation, the rate of repost is half (0.48, *P=.001)*. Posts that are lengthier are usually shared more (1.0002, *p<0.005)*; however, posts from more polar users (0.22, *p<0.005)* do not arouse as much discussion, suggesting the forum is relatively averse to echo chambering in relation to misinformation.

Table 3. Predictors of breadth (n=2,422).

Variables	Breadth		
Information Type	Exp(coef)	SE	*P*
True Information (baseline)	-		
Misinformation	1.10	0.085	.282
Disinformation	0.48	0.227	.001
Propaganda	2.07	0.063	<.001

Fabricate Information	0.79	0.156	.124
Conspiracy	1.23	0.132	.115
Control variables			
Word Count (of post)	1.0002	$0.25 * 10^{-4}$	<.001
User Activeness (number of historical posts)	0.998	$0.53 * 10^{-4}$	.001
Polarity of user	0.22	0.202	<.001

3 Node-level predictors of polarity

There are two graphs presented, one of the entire network (Figure 2, top) and one of the core network of more than 10 posts (Figure 2, bottom). The first finding is that overall, the entire network is less polarised than the core network, as exemplified by the lower average polarity score. This means most of the active users are polarized, they will post predominantly on exclusively true information or misinformation threads. The second finding is that trends for indegree follow that of betweenness centrality, but only after the top 15% of users are cut. This trend only appears when the core network is used. The third finding is that when using outdegree as the metric for influence, polarity decreases the most as top influential users are removed from the network.

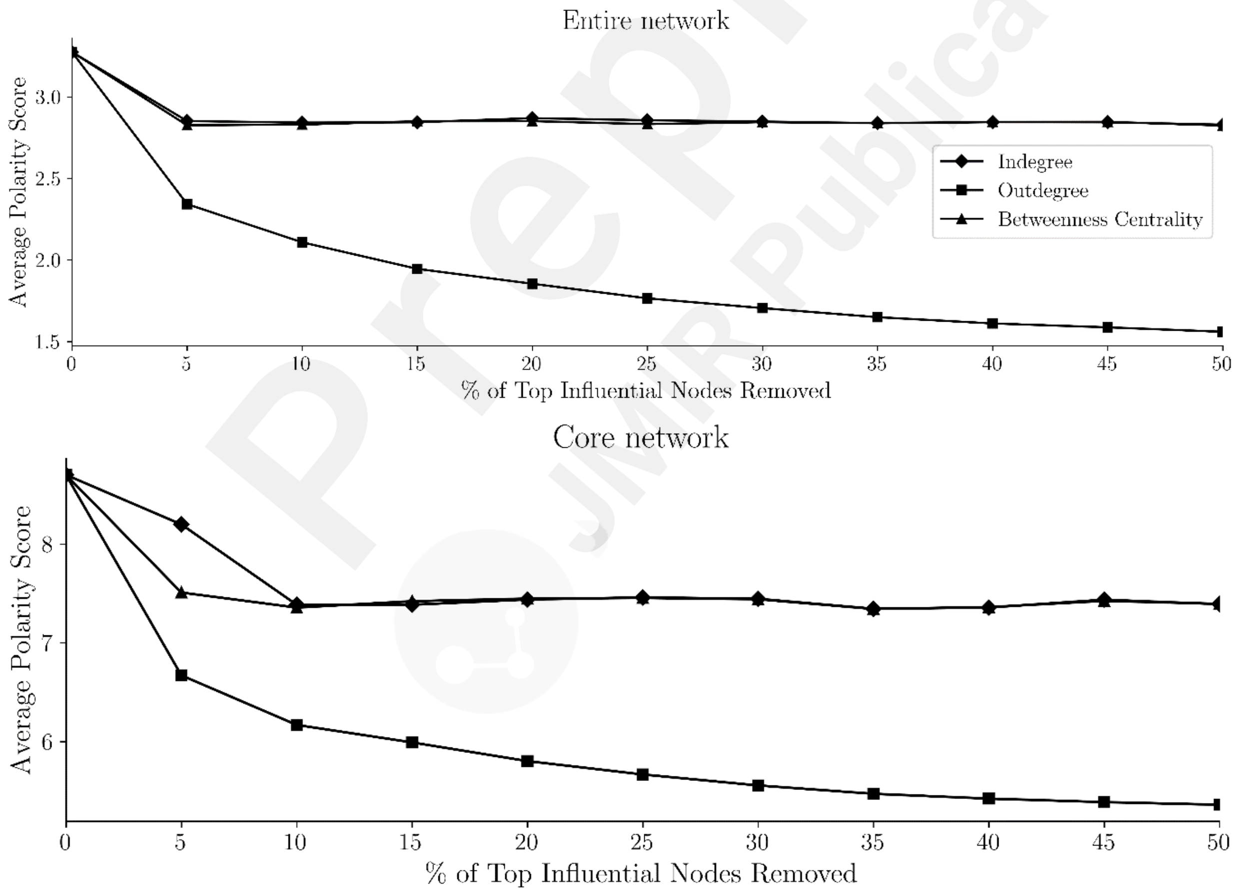

Figure 2. Impact of removing top percent of influential nodes on network (polarity score calculation: absolute value of volume)

These results suggest several trends. The first is that the core network exhibits more echo chambering in their behaviour, as indicated from the jump from an average starting point of 3.5 to

8.5. Thus, those that are more active on PTT are more likely to be more polar, gravitating towards true or false information. However, when interpreted in conjunction with the regression results, these polarised posts are likely to arouse less attention, suggesting a protective effect or breaking of echo chambering. The second is that polarisation happens with a few key users. In the core network, when the top 10% of nodes using any metric are cut, the polarity score decreases sharply. After 10%, the rate of decrease tapers off. The steeper declines for outdegree and betweenness centrality suggest that identifying active commenters and brokers in the network may be more useful than identifying those that receive many comments.

Discussion

This chapter aims to explore vaccine misinformation in Taiwan in three ways. First is a cataloguing of the types of vaccine misinformation encountered during the pandemic. Second is comparing the diffusion of true and false information. Third is measuring how influential users contribute to the level of polarity of the discussion forum.

The results from the regression supplement the literature on misinformation virality (Vosoughi et al., 2018) by that misinformation *type* may contribute to differences in breadth. Misinformation propagated with political propaganda intentions have higher rates of reposting compared to true information. This, in part, could be due to the nature of the PTT forum, which is a heavily politicised forum. Nevertheless, the finding that disinformation was reposted less suggests that certain streams of misinformation may have more viral potential than others. The findings for content on diffusion corroborate other literature findings of longer posts being more transmissible. Posts with longer text are more likely to be spread (Berger & Milkman, 2012). However, more active users generally have proportionally less of their boards arouse attention, a finding different from other platforms like Twitter (Suh et al., 2010). This could be a natural trend for users whose post volumes are high.

Other findings similar to previous studies include the more prevalent engagement with misinformation compared to true information (Gori et al., 2021; Hou et al., 2021; Karapetiantz et al., 2020; Yiannakoulias et al., 2019), as suggested by the skew of the graph in Figure 1, left. This is true despite most boards containing true information. In addition, this study finds that most misinformation streams also tend to be in either vaccine hesitant or anti-vaccination stance boards (C. H. Basch et al., 2017; Bradshaw et al., 2020; Yousefinaghani et al., 2021), a finding not surprising given the affinity of misinformation to an anti-vaccination agenda (Yin, 2022). Another new finding is that “brokers” of forum information – influential users as measured by betweenness – disproportionately engage with true information or misinformation across the entire network, suggesting that they are the polarising forces in echo chambering of misinformation. The findings suggest two main modes of moving forward in vaccine misinformation management.

The first is the implementation of a consolidated, automatic early detection system of online media potentially containing vaccine misinformation. Much like a disease surveillance system, a misinformation surveillance system should be able to detect and flag potential misinformation early such that their transmission is inhibited if necessary. The reason this is useful is because of the seeming affinity that misinformation has in attracting users, which is more dangerous when those users are influential. Once detected, this information can be used to inform publics as a means of “psychological inoculation” to help internet users better discern misinformation (Roozenbeek et al., 2022). Given that the narratives of misinformation are not novel in Taiwan, this system can be trained using global reports of vaccine-related misinformation in addition to the civilian-led misinformation clarification platforms already present in Taiwan (MyGoPen, CoFacts, *etc.)*. This management system would be particularly important during outbreaks or other flashpoints as online information often peaks as a response to events (Deiner et al., 2019; Diaz et al., 2021; Furini, 2021; Odone et al., 2018). As a step in infodemic management, it would help improve health literacy.

The second is to create a system that can identify then neutralise influential brokers (*i.e.*, high betweenness centrality) and commenters (*i.e.*, high outdegree) who have high interactions with misinformation posts. This can reduce the polarity in the network away from negative polarity. In this study, their connectivity means that neutralisation may reduce the polarity of the network. Identifying users that are either anti-vaccination or spreaders of misinformation using these metrics represents an untapped potential for positive engagement that continually breaks the echo chamber effect for both vaccine stance and misinformation spread.

While the technical aspects of such a system are relatively straightforward, the challenge extends beyond just technical regulation and public health, requiring the balancing of ethical considerations in moderating harmful information without impinging on free speech. This moral dilemma has been studied in other contexts such as politics (Kozyreva et al., 2023), suggesting that publics support misinformation management if it causes harm, defined as something undermining people's ability to make informed decisions (particularly around public health and elections) (European Commission, 2020). Studies on the association of misinformation and vaccine intention suggest that they are negatively correlated (Chen et al., 2022; Loomba et al., 2021). Other considerations are the scope of required management, such as removal of posts or the temporary or permanent suspension of users. During COVID-19, many social media platforms (*e.g.*, Facebook, Instagram) assumed this regulatory role and intervened to prevent the spread of misinformation and conspiracies around vaccines. However, in Taiwan, no such action was taken to actively manage misinformation on local platforms. Rather, the government provided information platforms as secondary references for those already exposed. Moving forward, misinformation management should constitute part of the overall architecture for epidemic management in Taiwan, a process likely to involve fierce democratic discussion or debate on the moral dilemma of speech regulation.

One major limitation of this study is the potentially insular nature of PTT. While PTT is a common board in Taiwan, it is not used by everyone. – a general trend for social media platforms Further studies should comparatively assess these same metrics against other platforms in Taiwan or elsewhere – or, against another topic within PTT – to understand whether platform users or platform mechanics may change the results on diffusion of misinformation and network polarity. Comparative analyses make the findings more robust by eliminating any echo chambering effect that may arise from the platform itself. Another potential limitation is the structure of the forum data itself, which may restrict conducting a full set of measures, such as the case with measuring diffusion depth and speed. More comparative studies may alleviate these system-based limitations.

Acknowledgements

This research was funded by City University of Hong Kong, grant number 7005826.

Conflicts of interest

The authors declare no conflict of interest.

References

Baines, A., Ittefaq, M., & Abwao, M. (2021). #Scamdemic, #Plandemic, or #Scaredemic: What Parler Social Media Platform Tells Us about COVID-19 Vaccine. *Vaccines*, *9*(5), 421. https://www.mdpi.com/2076-393X/9/5/421/htm

Bakshy, E., Rosenn, I., Marlow, C., & Adamic, L. (2012). The Role of Social Networks in Information Diffusion. *WWW'12 - Proceedings of the 21st Annual Conference on World Wide Web*, 519–528. https://arxiv.org/abs/1201.4145v2

Basch, C. H., Zybert, P., Reeves, R., & Basch, C. E. (2017). What do popular YouTube TM videos say about vaccines? *Child: Care, Health and Development*, *43*(4), 499–503. https://pubmed.ncbi.nlm.nih.gov/28105642/

Basch, Corey H., Meleo-Erwin, Z., Fera, J., Jaime, C., & Basch, C. E. (2021). A global pandemic in the time of viral memes: COVID-19 vaccine misinformation and disinformation on TikTok. *Human Vaccines & Immunotherapeutics*, *17*(8), 2373–2377. https://pubmed.ncbi.nlm.nih.gov/33764283/

Berger, J., & Milkman, K. L. (2012). What Makes Online Content Viral? *Https://Doi.Org/10.1509/Jmr.10.0353*, *49*(2), 192–205. https://journals.sagepub.com/doi/10.1509/jmr.10.0353

Bessi, A., Coletto, M., Davidescu, G. A., Scala, A., Caldarelli, G., & Quattrociocchi, W. (2015). Science vs Conspiracy: Collective Narratives in the Age of Misinformation. *PLOS ONE*, *10*(2), e0118093. https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0118093

Bessi, A., Petroni, F., Del Vicario, M., Zollo, F., Anagnostopoulos, A., Scala, A., Caldarelli, G., & Quattrocciocchi, W. (2014). Viral Misinformation: The Role of Homophily and Polarization. *WWW 2015 Companion - Proceedings of the 24th International Conference on World Wide Web*, 355–356. https://arxiv.org/abs/1411.2893v1

Bradshaw, A. S., Treise, D., Shelton, S. S., Cretul, M., Raisa, A., Bajalia, A., & Peek, D. (2020). Propagandizing anti-vaccination: Analysis of Vaccines Revealed documentary series. *Vaccine*, *38*(8), 2058–2069. https://pubmed.ncbi.nlm.nih.gov/31980194/

Bruns, A. (2017). Echo chamber? What echo chamber? Reviewing the evidence. *6th Biennial Future of Journalism Conference (FOJ17)*.

Chen, Y. P., Chen, Y. Y., Yang, K. C., Lai, F., Huang, C. H., Chen, Y. N., & Tu, Y. C. (2022). The Prevalence and Impact of Fake News on COVID-19 Vaccination in Taiwan: Retrospective Study of Digital Media. *Journal of Medical Internet Research*, *24*(4). https://pubmed.ncbi.nlm.nih.gov/35380546/

Choi, D., Chun, S., Oh, H., Han, J., & Kwon, T. "Taekyoung." (2020). Rumor Propagation is Amplified by Echo Chambers in Social Media. *Scientific Reports 2020 10:1*, *10*(1), 1–10. https://www.nature.com/articles/s41598-019-57272-3

Colleoni, E., Rozza, A., & Arvidsson, A. (2014). Echo Chamber or Public Sphere? Predicting Political Orientation and Measuring Political Homophily in Twitter Using Big Data. *Journal of Communication*, *64*(2), 317–332. https://onlinelibrary.wiley.com/doi/full/10.1111/jcom.12084

Davies, P., Chapman, S., & Leask, J. (2002). Antivaccination activists on the world wide web. *Archives of Disease in Childhood*, *87*(1), 22–25. https://pubmed.ncbi.nlm.nih.gov/12089115/

De Domenico, M., Lima, A., Mougel, P., & Musolesi, M. (2013). The Anatomy of a Scientific Rumor. *Scientific Reports 2013 3:1*, *3*(1), 1–9. https://www.nature.com/articles/srep02980

De Meo, P., Ferrara, E., Fiumara, G., & Provetti, A. (2013). Mixing local and global information for community detection in large networks. *Journal of Computer and System Sciences*, *80*(1), 72–87. https://arxiv.org/abs/1303.1738v2

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 Informatics Journal*, *25*(3), 1116–1132. https://pubmed.ncbi.nlm.nih.gov/29148313/

Diaz, P., Reddy, P., Ramasahayam, R., Kuchakulla, M., & Ramasamy, R. (2021). COVID-19 vaccine hesitancy linked to increased internet search queries for side effects on fertility potential in the initial rollout phase following Emergency Use Authorization. *Andrologia*, *53*(9). https://pubmed.ncbi.nlm.nih.gov/34181273/

Difonzo, N. (2018). Conspiracy rumor psychology. *Conspiracy Theories and the People Who Believe Them*, 257–268. https://www.researchgate.net/publication/329816708_Conspiracy_Rumor_Psychology

DiFonzo, N., Suls, J., Beckstead, J. W., Bourgeois, M. J., Homan, C. M., Brougher, S., Younge, A. J., & Terpstra-Schwab, N. (2014). Network structure moderates intergroup differentiation of stereotyped rumors. *Social Cognition*, *32*(5), 409–448.

Donzelli, G., Palomba, G., Federigi, I., Aquino, F., Cioni, L., Verani, M., Carducci, A., & Lopalco, P. (2018). Misinformation on vaccination: A quantitative analysis of YouTube videos. *Human Vaccines & Immunotherapeutics*, *14*(7), 1654–1659. https://www.tandfonline.com/doi/abs/10.1080/21645515.2018.1454572

European Commission. (2020). *Proposal for a regulation of the European Parliament and of the Council on a single market for digital services*. https://eur-lex.europa.eu/legal-content/en/ALL/?uri=CELEX%3A52020PC0825

Everett, M. G., & Valente, T. W. (2016). Bridging, brokerage and betweenness. *Social Networks*, *44*, 202–208.

Fine, G. A. (2007). Rumor, Trust and Civil Society: Collective Memory and Cultures of Judgment. *Http://Dx.Doi.Org/10.1177/0392192107073432*, *54*(1), 5–18. https://journals.sagepub.com/doi/10.1177/0392192107073432

Friedlander, E. R. (2001). Opposition to immunization: A pattern of deception. *Scientific Review of Alternative Medicine*, *5*(1), 18–23.

Furini, M. (2021). Identifying the features of ProVax and NoVax groups from social media conversations. *Computers in Human Behavior*, *120*, 106751.

g0v. (2023). *Cofacts: search “vaccine” (Chinese: □□□□ “□□”)*. https://cofacts.tw/search?type=messages&q=□□

Gori, D., Durazzi, F., Montalti, M., Di Valerio, Z., Reno, C., Fantini, M. P., & Remondini, D. (2021). Mis-tweeting communication: a Vaccine Hesitancy analysis among twitter users in Italy. *Acta Bio-Medica : Atenei Parmensis*, *92*(S6), e2021416. https://pubmed.ncbi.nlm.nih.gov/34739459/

Granovetter, M. S. (1973). The Strength of Weak Ties. *American Journal of Sociology*, *78*(6), 1360–1380. https://www.jstor.org/stable/2776392?typeAccessWorkflow=login

Hou, Z., Tong, Y., Du, F., Lu, L., Zhao, S., Yu, K., Piatek, S. J., Larson, H. J., & Lin, L. (2021). Assessing COVID-19 Vaccine Hesitancy, Confidence, and Public Engagement: A Global Social Listening Study. *J Med Internet Res*, *23*(6), e27632. https://www.jmir.org/2021/6/e27632

Jiang, X., Su, M. H., Hwang, J., Lian, R., Brauer, M., Kim, S., & Shah, D. (2021). Polarization Over Vaccination: Ideological Differences in Twitter Expression About COVID-19 Vaccine Favorability and Specific Hesitancy Concerns: *Social Media and Society*, *7*(3). https://journals.sagepub.com/doi/full/10.1177/20563051211048413

Karapetiantz, P., Audeh, B., Lillo-Le Louët, A., & Bousquet, C. (2020). Discrepancy Between Personal Experience and Negative Opinion with Human Papillomavirus Vaccine in Web Forums. *Studies in Health Technology and Informatics*, *272*, 417–420. https://pubmed.ncbi.nlm.nih.gov/32604691/

Kata, A. (2010). A postmodern Pandora’s box: anti-vaccination misinformation on the Internet. *Vaccine*, *28*(7), 1709–1716. https://pubmed.ncbi.nlm.nih.gov/20045099/

Kim, I., & Valente, T. W. (2020). COVID-19 Health Communication Networks on Twitter: Identifying Sources, Disseminators, and Brokers. *Connections*, *40*(1), 129–142.

Kozyreva, A., Herzog, S. M., Lewandowsky, S., Hertwig, R., Lorenz-Spreen, P., Leiser, M., & Reifler, J. (2023). Resolving content moderation dilemmas between free speech and harmful misinformation. *Proceedings of the National Academy of Sciences of the United States of America*, *120*(7), e2210666120. https://www.pnas.org/doi/abs/10.1073/pnas.2210666120

Lahouati, M., De Coucy, A., Sarlangue, J., & Cazanave, C. (2020). Spread of vaccine hesitancy in France: What about YouTube™? *Vaccine*, *38*(36), 5779–5782. https://pubmed.ncbi.nlm.nih.gov/32682617/

Lee, S. K., Sun, J., Jang, S., & Connelly, S. (2022). Misinformation of COVID-19 vaccines and vaccine hesitancy. *Scientific Reports 2022 12:1*, *12*(1), 1–11. https://www.nature.com/articles/s41598-022-17430-6

Loomba, S., de Figueiredo, A., Piatek, S. J., de Graaf, K., & Larson, H. J. (2021). Measuring the impact of COVID-19 vaccine misinformation on vaccination intent in the UK and USA. *Nature Human Behaviour 2021 5:3*, *5*(3), 337–348. https://www.nature.com/articles/s41562-021-01056-1

Meng, J., Peng, W., Tan, P. N., Liu, W., Cheng, Y., & Bae, A. (2018). Diffusion size and structural virality: The effects of message and network features on spreading health information on twitter. *Computers in Human Behavior*, *89*, 111–120.

MGP Fact Check Ltd. (2023). *MyGoPen: search "vaccine."* https://www.mygopen.com/search?q=□□

Odone, A., Tramutola, V., Morgado, M., & Signorelli, C. (2018). Immunization and media coverage in Italy: an eleven-year analysis (2007-17). *Human Vaccines and Immunotherapeutics*, *14*(10), 2533–2536.

Okuhara, T., Ishikawa, H., Okada, M., Kato, M., & Kiuchi, T. (2019). Japanese anti- versus pro-influenza vaccination websites: a text-mining analysis. *Health Promotion International*, *34*(3), 552–566. https://pubmed.ncbi.nlm.nih.gov/29584863/

Rogers, E. M. (1995). Diffusion of Innovations: Modifications of a Model for Telecommunications. *Die Diffusion von Innovationen in Der Telekommunikation*, 25–38. https://link.springer.com/chapter/10.1007/978-3-642-79868-9_2

Roozenbeek, J., van der Linden, S., Goldberg, B., Rathje, S., & Lewandowsky, S. (2022). Psychological inoculation improves resilience against misinformation on social media. *Science Advances*, *8*(34).

Schmidt, A. L., Zollo, F., Scala, A., Betsch, C., & Quattrociocchi, W. (2018). Polarization of the vaccination debate on Facebook. *Vaccine*, *36*(25), 3606–3612.

Shelby, A., & Ernst, K. (2013). Story and science. *Human Vaccines & Immunotherapeutics*, *9*(8), 1795–1801. https://www.tandfonline.com/doi/abs/10.4161/hv.24828

Suh, B., Hong, L., Pirolli, P., & Chi, E. H. (2010). Want to be retweeted? Large scale analytics on factors impacting retweet in twitter network. *Proceedings - SocialCom 2010: 2nd IEEE International Conference on Social Computing, PASSAT 2010: 2nd IEEE International Conference on Privacy, Security, Risk and Trust*, 177–184.

Taiwan FactCheck Foundation. (2023). *Taiwan FactCheck Center (□□□□□□□□).* https://tfc-taiwan.org.tw/taxonomy/term/475

Törnberg, P. (2018). Echo chambers and viral misinformation: Modeling fake news as complex contagion. *PLOS ONE*, *13*(9), e0203958. https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0203958

Tustin, J. L., Crowcroft, N. S., Gesink, D., Johnson, I., Keelan, J., & Lachapelle, B. (2018). User-Driven Comments on a Facebook Advertisement Recruiting Canadian Parents in a Study on Immunization: Content Analysis. *JMIR Public Health and Surveillance*, *4*(3). https://pubmed.ncbi.nlm.nih.gov/30249585/

Van den Bulte, C. (2000). New product diffusion acceleration: Measurement and analysis. *Marketing Science*, *19*(4), 366–380.

van der Linden, S., Dixon, G., Clarke, C., & Cook, J. (2021). Inoculating against COVID-19 vaccine misinformation. *EClinicalMedicine*, *33*. http://www.thelancet.com/article/S2589537021000523/fulltext

Vosoughi, S., Roy, D., & Aral, S. (2018). The spread of true and false news online. *Science*, *359*(6380), 1146–1151.

Wawrzuta, D., Jaworski, M., Gotlib, J., & Panczyk, M. (2021). What Arguments against COVID-19 Vaccines Run on Facebook in Poland: Content Analysis of Comments. *Vaccines*, *9*(5). https://pubmed.ncbi.nlm.nih.gov/34068500/

Weng, L., Menczer, F., & Ahn, Y. Y. (2013). Virality Prediction and Community Structure in Social Networks. *Scientific Reports 2013 3:1*, *3*(1), 1–6. https://www.nature.com/articles/srep02522

Whitehead, H. S., French, C. E., Caldwell, D. M., Letley, L., & Mounier-Jack, S. (2023). A systematic review of communication interventions for countering vaccine misinformation. *Vaccine*, *41*(5), 1018–1034.

Yang, J., & Counts, S. (2010). Predicting the Speed, Scale, and Range of Information Diffusion in Twitter. *Proceedings of the International AAAI Conference on Web and Social Media*, *4*(1), 355–358. https://ojs.aaai.org/index.php/ICWSM/article/view/14039

Yiannakoulias, N., Slavik, C. E., & Chase, M. (2019). Expressions of pro- and anti-vaccine sentiment on YouTube. *Vaccine*, *37*(15), 2057–2064.

Yin, J. D.-C. (2022). Media Data and Vaccine Hesitancy: Scoping Review. *JMIR Infodemiology*, *2*(2), e37300. https://infodemiology.jmir.org/2022/2/e37300

Yousefinaghani, S., Dara, R., Mubareka, S., Papadopoulos, A., & Sharif, S. (2021). An analysis of COVID-19 vaccine sentiments and opinions on Twitter. *International Journal of Infectious Diseases*, *108*, 256–262.

Zhang, L., & Peng, T.-Q. (2015). Breadth, depth, and speed: diffusion of advertising messages on microblogging sites. *Internet Research*, *25*(3), 453–470.

Zhao, S., Hu, S., Zhou, X., Song, S., Wang, Q., Zheng, H., Zhang, Y., & Hou, Z. (2023). The Prevalence, Features, Influencing Factors, and Solutions for COVID-19 Vaccine Misinformation: Systematic Review. *JMIR Public Health Surveill 2023;9:E40201 Https://Publichealth.Jmir.Org/2023/1/E40201*, *9*(1), e40201. https://publichealth.jmir.org/2023/1/e40201

Zimmerman, R. K., Wolfe, R. M., Fox, D. E., Fox, J. R., Nowalk, M. P., Troy, J. A., & Sharp, L. K. (2005). Vaccine criticism on the world wide web. *Journal of Medical Internet Research*, *7*(2).

Zimmerman, T., Shiroma, K., Fleischmann, K. R., Xie, B., Jia, C., Verma, N., & Lee, M. K. (2023). Misinformation and COVID-19 vaccine hesitancy. *Vaccine*, *41*(1), 136–144.

Abbreviations

N/A