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Predicting Health Communication Patterns in Follower–Influencer Networks: The Case of Taiwan Amid COVID-19[1]

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Abstract

As netizens increasingly utilize social media to obtain and engage with information, this study aims to determine the extent to which the follower–influencer interaction is manifested and strengthened. To analyze information related to the novel coronavirus disease (COVID-19), a total of 62,119 online posts from 11 Internet forums were examined to find a relationship between followers and influencers in Taiwan. These forums are PTT, SOGO, Ck101, Plurk, Mobile01, TalkFetnet, Gamez, PlaySport, Dcard, Eyny, and PCDVD. The variables that were the best predictors of influencer classification were *strong influences*, *engagements*, and *hot values* across 11 Internet forums. Learning the response to the COVID-19 pandemic is vital because public actions could have been fueled by stigmatizing terms that may harm public health and well-being. The results questioned the conventional diffusion of traditional news sources because the influencers brought widespread attention to the health threat issues in the early outbreak stages. This study enhances the understanding of forum types, follower engagement, and influencers' impact maximization in social networks. The conclusion provides insight into the relationships and information diffusion mechanisms to ensure accurate health information dissemination.

Keywords: followership, risk communication, Internet forum, engagement, health information, COVID-19

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Background

According to the Johns Hopkins Coronavirus Resource Center (2020), as of July 22, 2020, the novel coronavirus disease (COVID-19) has infected over 9.0 million individuals globally, with a death toll over 615,462. As countries, regions, and health care professionals struggle to tackle the highly transmissible and largely unknown virus, the public has to react and respond to their everyday health concerns. During the COVID-19 pandemic, social media have provided increasingly important platforms for learning about current information and breaking news on health risks (Cinelli et al., 2020; Depoux et al., 2020; Zubiaga, 2019).The present study aims to examine the path of COVID-19 information dissemination and development in Internet forums. Further, we proposed to predict online users' interaction amid the emerging viral disease to learn more about the formation of online public discourse regarding health concerns.

Taiwan Users' Profile and Online Media Landscape

The percentage of individuals aged ≥12 years with Internet access has reached 82.0% of the population in Taiwan, accounting for approximately 19.27 million people, whereas 15.2 million are active users of social media, as reported by Taiwan Network Information Center (TWNIC) in 2019. The number of social media users is inversely proportional to age, with higher use rates among those in the 12-23 age range. In Taiwan, the younger generation aged 12-23 years are most likely to use social media, (95.5%), followed by those aged 24-38 (94.5%) and 39-54 years (81.0%) (TWNIC, 2019). Internet forums are critical social media, designed to build online communities of lay and young users with similar interests, such as health crises (L. X. Li, 2014; Wang et al., 2010). Every discussion forum analyzed in this research is an independent entity and not affected by corporate influences like Twitter, Facebook, or YouTube are.

Literature Overview

Conventional diffusion theory proposes that a minority of people are generally the most critical factors affecting information cascades (Zhao et al., 2014). Information diffused in online social media seems to complicate the influence and interaction of online participants. An example of information dissemination on Weibo for the Chinese shows that the opinion leaders have many followers by a two-step procedure in spreading information (Zhang et al., 2016). A follower is an individual who follows and adheres to the opinions or ideas of others (i.e., influencers), whereas active influencers have the power to disseminate information to persuade followers (Case et al., 2004; Huffaker, 2010). The interplay study between influencers and followers has been common for marketing actions (e.g., Lou & Alhabash, 2020; Lou et al., 2019) but rare in health communication (e.g., Blakemore et al., 2020).

Influencers and their followers can interact closely by discussing the latest news and events, as well as sharing and distributing specific related topics (Burt, 1999;

Tanner, 2001; Weeks et al., 2017). News remains the primary source of information for netizens in setting agenda and frames for online discourse (Zhang et al., 2016; Zhou & Moy, 2007). Online influencers may share the news source to initiate discussion and provide guidance through discussions to form collective opinions (Huffaker, 2010; Schäfer & Taddicken, 2015). Influencers can build a discussion framework by shaping the shared content on a specific topic.

As counterparts to online influencers, followers can further engage by browsing the text, expressing their opinions, making comments, and sharing news within the networks (Welbers & Opgenhaffen, 2019). Studies have identified several important factors in attracting follower engagements by tracking posts, hits, likes, and comments made to influencers (Huffaker, 2010; Peacock & Leavitt, 2016; Yoo & Alavi, 2004). To fill the gap in providing the relevant measurement of follower-influencer social networks, the present study explores how influencers and followers interact in online forums, particularly during the COVID-19 outbreak. Given the impact of the online discussion on health issues, we intend to determine the effectiveness of risk communication during the pandemic stages. In line with our research objectives, four research questions (RQs) were raised about the relationship between influencers and followers over the past three months:

RQ1: How do the main Internet forums mention COVID-19 and related topics?

RQ2: What proportion of COVID-19 discussions in Internet forums employ news sources?

RQ3: How does the overall mechanism of the follower-influencer relationship interact when disseminating COVID-19 related messages?

RQ4: What are moderating factors for predicting the follower-influencer relationships?

Method

An Internet forum is an online discussion site where users with common interests can hold conversations in the form of posted messages. A discussion forum is tree-like in structure, meaning it contains several sub-forums along with several topics. They are close to regular people's daily life, reflecting quickly the opinions of netizens in the online community, which is different from the large-scale social media portal websites (Preece & Maloney-Krichmar, 2003). To some extent, Internet forums are open spaces with free access, fast circulation, and an interactive mechanism for information dissemination (Choi, 2015; Kim & Yoon, 2011).

In Taiwan, the most notable and significant Internet forum communities have converged on the themes of news, technology, health, and academic content, and have also recruited a large number of visitors. Based on the aforementioned criteria, this study screened 11 forums from the list of top websites in Taiwan as one of the most popular channels of information sharing. We also considered that these 11 forums are the most active and used forums by Taiwanese netizens (SimilarWeb Website Ranking, 2020); for instance, PTT is observed to be one of the largest terminal-based bulletin board systems with 3.3 million users, followed by Mobile01 forum with 3.0 million users; Dcard with 2.3 million users, and Eyny with 1.6 million visitors every month. Thus, the sample included PTT, SOGO, Ck101, Plurk, Mobile01, TalkFetnet, Gamez, PlaySport, Dcard, Eyny, and PCDVD. Detailed information about the forums is listed in Appendix I.

Data were collected via the bottom-up method by adopting text mining to retrieve posts on COVID-19 and its related keywords. Valid posts that contained the following eight variables were included: *forum type*, *words*, *days*, *influences*, *hits*, *comments*, *engagements*, and *hot value*. The operational definition of these terms is listed in Appendix II. The timeframe chosen for this study was from December 30, 2019, to March 31, 2020, taking into consideration information sources for public response about COVID-19 risks. A total of 42 keywords were employed based on earlier references cited in screening for the variable measurement. The keywords are listed in Appendix Ⅲ.

In addition, automated content analysis using uMiner was employed to identify the prominent issues and interactions among users. uMiner is a tailored platform based in Taiwan that supports the implementation of a coding taxonomy for measuring variables, such as hits, comments, engagements, and hot value. Therefore, uMiner embedded natural language processing was employed to investigate online contents in their natural setting. It is noteworthy that the process involved pilot coding, modification of the coding scheme, double coding, and manual proofreading (Chang et al., 2019; Kumar & Garg, 2019). The procedure ensured the efficiency and validity of capturing opinions from the text in syntactically correct and explicit language. Notably, coders manually labeled and randomly checked approximately 500 sampled posts and then used the uMiner classifier to implement the filtering process. The classification accuracy level reached 82%, which is acceptable (Cui et al., 2015).

Data were further analyzed using SPSS Version 24.0 for descriptive analysis and a regression model was used to determine the relationship between a single dependent (criterion) variable and more independent (predictor) variables. Although different algorithmic formulas show corresponding changes for the hot value in concrete scenarios, as seen in microblogs (Song & Meng, 2015), news websites (Liang & Lai, 2002), and online forums (Cao & Tang, 2014), the analysis yields a predicted value for the criterion variable resulting from a linear combination of predictors. Computational communication research has emphasized the hot value of related topics by weighting engagements (Preece & Maloney-Krichmar, 2003). In this method, the assignment of weights significantly impacts the final quantification results. The measurement of valid posts that contained other variables, including influences, hits, comments, and engagements, leads to a closed-loop structure of information flow factors in online forums by attracting and facilitating more interactions (Butler, 2001; Huffaker, 2010).

Results

A total of 62,119 online posts on the COVID-19 outbreak from the interplay of follower–influencers networks in 11 Internet forums were investigated. Six prominent themes were further classified by deductive analysis: diseases; infection prevention and treatment; policy; politicians and non-political figures; news agency and research institute; and incidence and event. The most frequent themes were on COVID-19 and its related topics (71.9%), followed by infection prevention and treatment (42.7%) and policy (33.7%). The network of posted content features and users' behavior statistics were observed to determine the interplay of follow-ship in Internet forums. Seven forums—namely, *PTT*, *SOGO*, *Ck101*, *Plurk*, *Mobile01*, *Dcard*, and *Eyny*—were the most frequently used platforms for COVID-19 related discussion.

The descriptive analysis of the attributes of COVID-19 messages is presented in Table 1 as means, standard deviations (SDs), and maximum and minimum of ranges.

Table 1

Descriptive Analysis of Attributes of COVID-19 Messages Presented in 11 Internet Forums

Variable	Mean	SD	Maximum	Minimum
Words	413.2	370.7	2799	69
Days	46.1	25.8	90	3
Influences	415.4	547.8	3049.8	0
Hits	71.1	185.1	775	0
Comments	44.1	70.9	391	0
Engagements	45.0	70.5	391	0
Hot value	45.6	70.2	391	0

One venue, PTT, had the majority share of posts among users (68.5%), followed by Mobile01 (9.0%) and Eyny (6.7%). The top posts from numerous sub-forums of PTT showed that the most frequently used keywords included the stigmatizing term *Wuhan pneumonia* (29.7%), followed by *coronavirus* (26.6%) and *epidemic* (25.0%). Over half of all posts (58.4%) quoted traditional news media sources, and the average length of a forum post was 413.2 Chinese characters. The average number of influences, hits, and comments received by a post was 415.4, 71.1, and 44.1 times, respectively.

A multiple regression analysis was conducted to check if the text level and forum type predicted the total value of influences. The analysis results showed that a single dependent variable (influences) was positively predicted by followers' behavior in Taiwan's Internet forums (B = .12, SE = .00, t = 44.90, p < .001). Furthermore, two hierarchical multiple regressions were conducted to analyze the variables of the length of words, posting time, and seven main forum venues, and opinion leaders' influences to explain 97% of the variance by the various predictor variables (R^2 = .97, F(9, 79) = 259.47, p < .001). We found that the level of influences explained a significant amount of the variance in followers' value. Table 2 shows the effect of the influences on followers' engagement in the hierarchical multiple regression.

Table 2

Effect of Influences on Followers' Engagement in Hierarchical Multiple Regression

Forum content & type	Unstandardized coefficients
Words	.00
Days	-.01
PTT	43.42***
SOGO	12.46
Ck101	-11.52
Plurk	7.85
Mobile01	40.79***
Dcard	31.41**
Influences	.12***

Note: **p < .01, ***p < .001
R^2 = .97, F(9, 79) = 259.47

The analysis showed that influencers' impact positively predicted the content with hot value in Taiwan's Internet forums. The relationship between followers' engagements and hot value of COVID-19 messages was significant (B = 1.00, SE = .00, t = 616.66, p < .001). Two hierarchical multiple regressions were conducted to analyze the variables, such as the length of words, posting time, and main forum venue; followers' engagements were observed to explain 100% of the variance using various predictor variables (R^2 = 1.00, F(9, 79) = 48309.34, p < .001). Table 3 shows the effect of followers' engagements on the content hot value in the hierarchical multiple regression.

Table 3

Effect of Followers' Engagements on Content Hot Value in Hierarchical Multiple Regression

Forum content & type	Unstandardized coefficients
Words	.00
Days	.00
PTT	-3.15***
SOGO	-.96
Ck101	.86
Plurk	-.54
Mobile01	-3.10***
Dcard	-2.38**
Engagements	1.00***

Note: **p < .01, ***p <.001
R^2 = 1.00, F(9, 79) = 48309.34

Table 4 shows the effect of hot value on influencers' impact in the hierarchical multiple regression.

Table 4

Effect of Hot Value on Influencers' Impact in Hierarchical Multiple Regression

Forum content & type	Unstandardized coefficients
Words	.01
Days	.02
PTT	-315.39***
SOGO	-96.12
Ck101	85.84
Plurk	-54.63
Mobile01	-310.09***
Dcard	-237.62**
Hot value	7.87***

Note: **p <.01, ***p <.001
R^2 = .97, F(9, 79) = 285.44

The hot value of COVID-19 messages positively predicted the relationship between followers and influencers. The interplay between followers and hot value of

COVID-19 messages was significant (B = 7.87, SE = .16, t = 48.56, $p < .001$). Furthermore, two hierarchical multiple regressions were conducted to analyze the followers' attributes, forum types, and hot values to explain 97% of the variance using various predictor variables (R2 = .97, F(9, 79) = 285.44, $p < .001$).

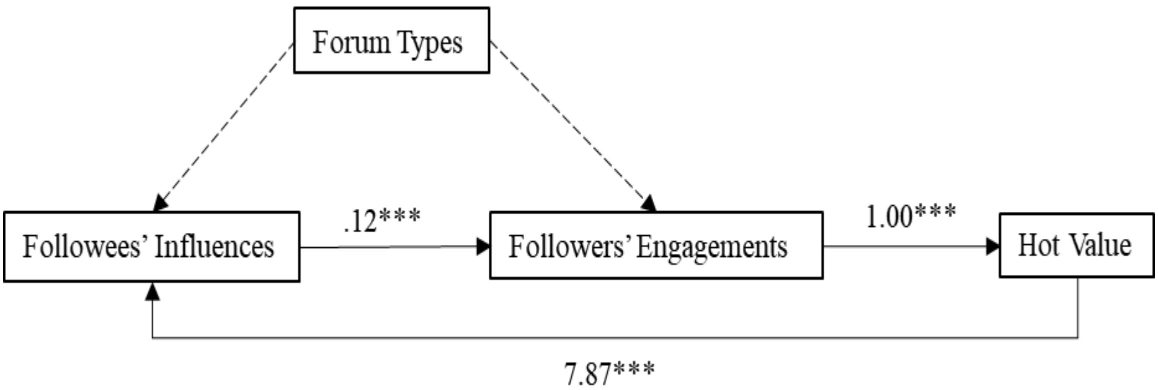
Research Findings and Discussion

As of June 27, 2020, Taiwan has recorded a relatively small number of 447 confirmed cases and 7 deaths associated with COVID-19 (Taiwan Centers for Disease Control, 2020). At the same time, COVID-19 has emerged as a dominant topic of discussion on Internet forums compared to other topics.

Figure 1 displays the relation construction that describes the information dissemination path in Internet forums and users' attributes related to COVID-19, with solid paths indicating significant relations ($p < .001$).

Figure 1

Relation Construction Between Users' Attributes and Dissemination Path of COVID-19 Messages



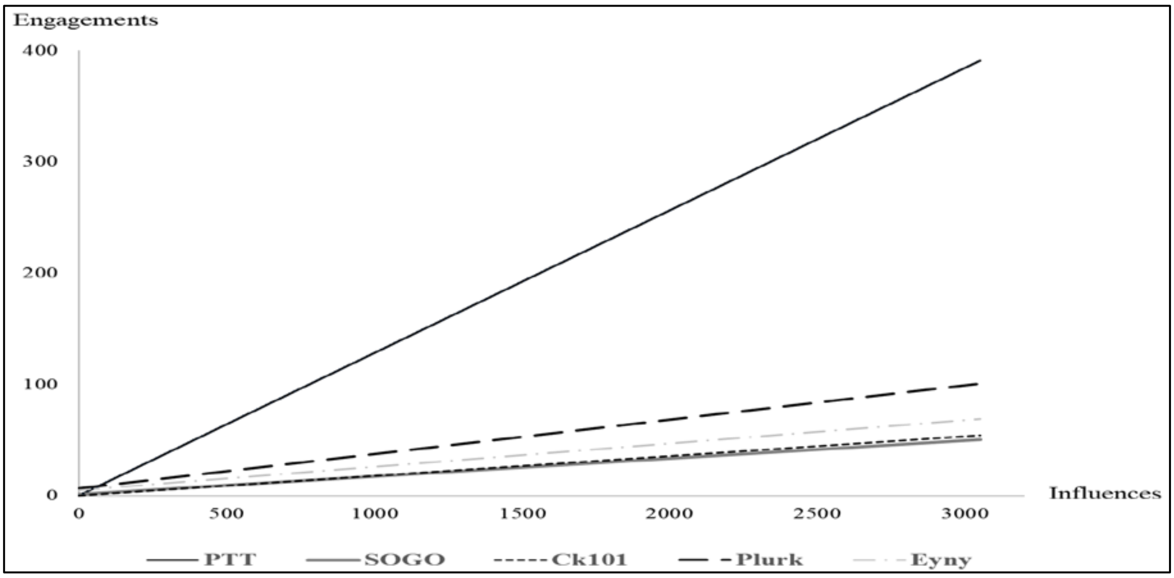
An in-depth comparison of the diffusion among different information paths suggested that opinion leaders' influence brought popular attention to the public health threat issues in the early stage of the outbreak, regardless of the large-scale news coverage on COVID-19. Inconsistent with earlier studies (e.g., Li et al., 2017), online news media play a relatively minor role in setting the agenda on COVID-19 as the primary source of information. In sum, the news did not exert as much influence on the online forum discourse as expected, because the followers and influencers did not significantly correspond to the news message content in the defined public sphere.

The linear effect of influencers' impacts on followers' engagements was significantly moderated by five online forums: PTT ($B = .10$, $SE = .00$, $t = 36.78$, $p < .001$); SOGO ($B = -.11$, $SE = .05$, $t = -2.11$, $p < .05$); Ck101 ($B = -.11$, $SE = .02$, $t = -4.53$, $p < .001$); Plurk ($B = -.09$, $SE = .02$, $t = -4.47$, $p < .001$); and Eyny ($B = -.10$, $SE = .01$, $t = -7.73$, p

< .001). Specifically, PTT had a positive moderating effect for strengthening the link between followers' and influencers' engagement, which was significantly higher compared with the other four forums. Figure 2 displays the comparison of the moderation effects of five forums on the relationship between influences and engagements.

Figure 2

Comparison of Moderation Effects of Five Forums on the Relationship Between Influences and Engagements



Conclusion

This study shows how COVID-19 related messages are discussed and disseminated among people on Internet forums. The COVID-19 outbreak has caused tremendous harm by adopting stigmatizing terms. Hence, learning the public response to the COVID-19 pandemic is vital, because public actions have been fueled by stigmatizing terms, biases, rumors, and misinformation that hurt public health and well-being. The present study provides an insight into the information flow for constructing the dissemination mechanism of communication regarding health risks. In this flow, followers of a social community actively sought information and comments in Internet forums. Influencers' impact was strongly reflected in their ability to attract and respond to followers in certain Internet forums.

This study has several limitations. First, its findings were not intended to be exhaustive. For a more thorough explanation of the analysis, data from other social networking platforms frequently used in Taiwan (i.e., Facebook, Line, or Instagram) should be considered to confirm and generalize the results. Second, in comparing various diffusions of information during different peaks of the COVID-19 outbreak, research that focuses on the proportions of the crowd and opinion leaders should be considered. Third, online forums are platforms where many young netizens share their ideas, serving as open online spaces for users to voluntarily express their opinions and respond to others' opinions. However, the intrinsic factors that drive these young netizens to participate in the adoption of slang words are not fully understood.

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Appendix I

	Chinese name of forum	English translation	2020 Ranking of top websites in Taiwan	Domain name	Average independent visitors per month in 2020	Forum description
1	批踢踢實業坊	PTT	13	ptt.cc	3.305 Million	Largest terminal-based bulletin board system (BBS) based in Taiwan
2	SOGO 論壇	SOGO	193	oursogo.com	352,880	Super popular leisure and entertainment forum, including taste of life, leisure world, hobbies, academic arts, women's channel, computer digital, game paradise
3	卡提諾論壇	Ck101	192	ck101.com	744,409	A comprehensive large-scale discussion area, with a variety of rich discussion boards and topics
4	Plurk	Plurk	84	plurk.com	745,337	A free social networking and micro-blogging service
5	Mobile01	Mobile01	25	mobile01.com	3.014 Million	Largest life website and forum, topics include cars, mobile phones, home decoration, digital equipment, real estate investment, etc.

	Chinese name of forum	English translation	2020 Ranking of top websites in Taiwan	Domain name	Average independent visitors per month in 2020	Forum description
6	鹿 talk 社	TalkFetnet	200-300	talk.fetnet.net	100,838	Telecommunications, 3C technology and smart life community
7	鐵之狂傲	Gamez	200-300	gamez.com.tw	33,736	Video games, consoles, and accessories
8	玩運彩	PlaySport	200-300	playsport.cc	33,613	Pure lottery exchange platform
9	Dcard	Dcard	30	dcard.tw	2.355 Million	Largest anonymous communication platform for young people, containing topics of current affairs, feelings, eating, drinking, playing, studying and working
10	伊莉論壇	Eyny	27	eyny.com	1.570 Million	Hot topics, leisure and entertainment, academic computer, information exchange, etc.
11	PCDVD 數位科技討論區	PCDVD	200-300	pcdvd.com.tw	36,966	Computer 3C technology and life information

Appendix II

Measurements

Forum type: Internet forum was recoded into one dummy variable. For example, PTT forum was coded as 1, and its sub-categories further coded as 1-2, 1-3, and so on.

Words: Length of content in a post

Days: Date and time when a post was made public (Song & Meng, 2015)

Influences: The average level of influence of opinion leaders in the industry, especially in changing the attitude or behavior of others after taking a particular action, including publishing, posting, commenting, and forwarding a piece of information (Huffaker, 2010; Yoo & Alavi, 2004).

Hits: Number of clicks of a posted item (Meijer & Kormelink, 2015)

Comments: Number of comments left on a post (Meijer & Kormelink, 2015)

Engagements: Frequency of involvement by weighted sum of hits and comments (Peacock & Leavitt, 2016; Welbers & Opgenhaffen, 2019)

Hot value: A "hot value" is used to learn the popularity index of a post from the time of posting to the present in the forum. It is affected by users' behavior in the same community within a limited time period (Li, et al., 2017; Liu et al., 2011; Ma et al., 2016; Song & Meng, 2015). A higher hot value is associated with a higher position of the corresponding page in the forum lists.

Appendix III

Codebook

1. 冠狀病毒 coronavirus
2. 新型冠狀病毒 novel coronavirus (nCoV)
3. 2019 新型冠狀病毒 2019 novel coronavirus (2019-nCoV)
4. 肺炎 pneumonia
5. 病毒性肺炎 viral pneumonia
6. 人傳人 person-to-person/human-to-human transmission
7. 潛伏期 incubation/latent period
8. 無症狀 silent/asymptomatic period
9. 飛沫傳播 droplet transmission
10. 接觸傳播 contact transmission
11. 醫院/院內感染 nosocomial infection; hospital-acquired infection
12. 確診病例 confirmed case
13. 疑似病例 suspected case
14. 發病率 incidence rate
15. 死亡率 mortality rate
16. 遏制疫情蔓延 to contain the outbreak
17. 封城 A city is on lockdown/A city goes into lockdown.
18. 延遲開學 to postpone the reopening of schools
19. 居家檢疫 (自我隔離) to quarantine yourself in your home; self-monitored quarantine
20. 疫苗 vaccine
21. 口罩/口罩實名制 wear a mask/mask purchase with identification required
22. 洗手/勤洗手 to wash your hands often/carefully
23. 消毒 disinfection
24. 避免去人多的地方 avoid crowds
25. 世界衛生組織 or 世衛組織 (WHO or who or 世衛) (World Health Organization)
26. 中國 (China)
27. 湖北 or 湖北省 (Hubei or Hubei province)
28. 武漢 (Wuhan)
29. 郵輪 (遊輪 or 威斯特丹 or 寶瓶星 or 世界夢 or 鑽石公主) (crises)

30. 台胞 or 台商 or 包機 or 台商包機 (cross-strait charter or Taiwan business people)
31. 中央 or 北京 (Central government or Beijing)
32. 共產黨 or 阿共 or 強國佬 (Communist Party or two other nicknames related to the Chinese Communist Party)
33. 台灣疾病預防控制中心/CDC (Center for Disease Control and Prevention in Taiwan, or CDC)
34. 醫療人員 (medical personnel or health workforce or health workers)
35. 鐘南山 (Zhong Nanshan)
36. 李文亮 (李醫師 or 吹哨人) (Li Wenliang or whistle blower)
37. 台灣政治人物 (蔡英文 or 總統 or 小英) (Taiwan political figures or Taiwan President or Tsai Ing wen)
38. 蘇貞昌 (蘇院長 or 衝衝衝 or 行政院長 or 行政院) (Soo Tsing Tshiong or Prime Minster)
39. 陳時中 (衛福部部長 or 部長 or 衛福部長) (Chen Shih Chung or Minister of Health and Welfare)
40. 藝人 (小 S or 徐熙娣 or 大 S or 大小 S or 范瑋琪 or 范范 or 范建 or 黑范) (names of some celebrities in Taiwan)
41. 新住民 or 外勞 or 外配 (new immigrants or foreign spouse)
42. 媒體 or 新聞 (media or news)

Biographical Notes

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