Investigating collective actions and mental health on social media during the 2019 anti-government social unrest in Hong Kong

Presenter: Ka Yu, Lam (Calvin), M.Phil Student | Supervisor: Dr. Christian Chan, Associate Professor

Department of Psychology, Faculty of Social Sciences, HKU

Background & Objective

Modern data science research utilizes text mining techniques for analyzing social media content on mental health issues and collective actions.[1,2] Using the social media content that was related to the 2019 anti-government social unrest in Hong Kong, current study revealed the associations between collective actions and mental health.

Methods: Materials

Users-generated comments on online forums (e.g. Baby-Kingdom Forum, Discuss.com.hk, Hong Kong Golden Forum, and LIHKG Forum) and social networking sites (e.g. Twitter) from June to November 2019 were obtained using Meltwater Database[3] and Python algorithms. For text mining the obtained comments, a Cantonese term-list was created to identify terminologies related to collective actions (e.g. street protest and propaganda) and mental health (e.g. sleep, acute stress, and mood disorder (depression, PTSD) symptoms.

Methods: Statistical Analyses

The frequencies of comments containing the currently interested terminologies were used to create time series data frames and were analyzed using autoregressive integrated moving average with explanatory variable (ARIMAX).[4] Adjustments (decomposition) for the data frames were made for addressing the seasonality and the stationarity. The statistical package R was used.

Results and Implications

Findings: A total of 3,572,665 social media comments was identified in the 183 days of investigation period, in which offline protests occurred on 75 days. ARIMAX results showed that the frequency of comments containing collective action terms was relatively higher on days with offline protests than on days without. The frequency of comments containing both collective action- and mental health-terms was also relatively higher on days with offline protests than on days without.

Implications: Current results suggest a positive association between offline protest activities and online social media content. Text mining the social media content may help identify the mental health needs deriving from social unrest.

Ongoing study: Study 2 has been conducting by using the social media content and the government data, and aims to reveal the associations among the frequencies of (1) police arms (e.g. tear gas and bullets), (2) collective actions, and (3) mental health. Implications for public policy and coping strategies for mental health will be discussed.

Table 1a. Comparisons between Numbers of Comments from Social Media during 1 June – 30 November 2019.

	Outcome Variable 1: Protest terms				Outcome Variable 2: Protest & mental health symptoms terms			
	Parameter	**Estimate**	**95% CI**	***p***	**Parameter**	**Estimate**	**95% CI**	***p***
(a). Online forums								
Crude model 1	(1,1,1) (1,0,1)				(1,0,0) (2,0,0)			
Protest dates		0.011	-0.024 – 0.047	0.537		-0.004	-0.054 – 0.046	0.869
Adjusted model 1*	..				(2,0,1) (2,0,0)			
Protest dates		..				**0.265**	**0.111 – 0.419**	**<0.001**
Crude model 2	(1,1,1) (1,0,1)				(1,0,0) (2,0,0)			
Violent protest dates		0.002	-0.049 – 0.054	0.935		-0.012	-0.034 – 0.115	0.747
Non-protest dates		-0.010	-0.055 – 0.035	0.662		-0.002	-0.065 – 0.085	0.939
Adjusted model 2*	..				(2,0,1) (2,0,0)			
Violent protest dates		..				-0.075	-0.227 – 0.076	0.333
Non-protest dates		..				**-0.294**	**-0.403 – -0.185**	**<0.001**

Table 1b. Comparisons between Numbers of Comments from Social Media during 1 June – 30 November 2019.

	Outcome Variable 1: Protest terms				Outcome Variable 2: Protest & mental health symptoms terms			
	Parameter	**Estimate**	**95% CI**	***p***	**Parameter**	**Estimate**	**95% CI**	***p***
(b). Social networking sites								
Crude model 3	(0,1,0) (0,0,0)				(4,1,2) (2,0,0)			
Protest dates		**0.180**	**0.085 – 0.275**	**< 0.001**		0.187	-0.067 – 0.062	0.070
Adjusted model 3*	..				(4,1,1) (1,0,0)			
Protest dates		..				0.270	-0.304 – 0.843	0.358
Crude model 4	(0,1,0) (0,0,0)				(4,1,1) (0,0,1)			
Violent protest dates		**0.221**	**0.086 – 0.355**	**0.002**		0.103	-0.163 – 0.369	0.448
Non-protest dates		-0.063	-0.180 – 0.054	0.293		-0.145	-0.387 – 0.096	0.239
Adjusted model 4*	..				(2,1,1) (2,0,1)			
Violent protest dates		..				0.059	-0.092 – 0.210	0.118
Non-protest dates		..				**-0.275**	**-0.390 – -0.160**	**<0.001**

Note. We used the ARIMAX models. CI: Confidence interval. Parameter for time series (p, q, d) and seasonality (P, Q, D).
*Reference group for each model: model 1 & 3 = Non-protest dates. Model 2 & 4 = dummy variables of "violent protest dates" and "non-protest dates"; and "other dates" as reference group.
Adjusted models: controlled for number of protest terms, and its interaction with protest dates and the reference group.

References

1. Ahmed S, Jaidka K, Cho J. Tweeting India's Nirbhaya protest: a study of emotional dynamics in an online social movement. Social Movement Studies 2017; 16(4): 447-65.
2. Budiyanto S, Sihombing HC, IM FR. Depression and anxiety detection through the Closed-Loop method using DASS-21. Telkomnika 2019; 17(4).
3. Meltwater News Hong Kong Ltd. Meltwater Database. Hong Kong; 2019.
4. Jebb AT, Tay L, Wang W, Huang Q. Time series analysis for psychological research: examining and forecasting change. Frontiers in psychology 2015; 6: 727.

Funding

General Research Fund, Research Grants Council, University Grants Committee of Hong Kong (RGC GRF Grant #17612718) and Public Policy Research Funding Scheme (Special Round), Policy Innovation and Co-ordination Office (#SR2020.A8.017).

Contact

Email: u3007239@connect.hku.hk