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RESEARCH ARTICLE

A text mining and machine learning study on the trends of and dynamics between collective action and mental health in politically polarized online environments

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Abstract
Social media and online forums play an increasingly important role in the mobilization of collective action. This study examined how the discussion of collective actions impacts the expression of psychological distress in politically polarized online environments. We used text mining and machine learning models to analyze 39,487,911 user-generated comments during the 2019 social unrest in Hong Kong on two online forums frequented by anti-government (Lihkg.com) and pro-government (Discuss.com.hk) netizens. Results from time-series models yielded two main findings. First, there was a time-lagged association between the discussion of protest and the mention of psychological distress on both forums. Second, on Discuss.com.hk but not Lihkg.com, fewer comments containing psychological distress were created on days with offline protests (especially on days with violent conflicts) than days without. Together, these findings suggest that politically polarizing environments contribute to psychological distress.

Keywords Collective actions · Psychological distress discourse · Political polarity · Social media · Text mining & machine learning · Time-series

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Introduction

Evidence suggests that political conflicts can heighten the risk of mental health problems [1]. The mental health risk is salient when individuals participated in protests [2], or if they were exposed to social unrest [3, 4], or unrest-related violence and stressors [5].

Social media can reveal important aspects of social unrest; Individuals discuss, organize, and express feelings about collective actions using social media platforms [3, 6–10]. The boundary between offline protests and online protests is increasingly blurred. Social media platforms become political environments for activists and their opponents to react and discuss ongoing events. The online and offline interaction may contribute to the development of collective actions and might also have mental health consequences [11].

The 2019 social unrest in Hong Kong provides an opportunity for studying online and offline interactions, as individuals utilized social media platforms to organize mass protests and share information [9, 11]. Specifically, it allows us to study how online political environments influence online discussions, given that offline protests may influence these online behaviors and the subsequent psychological consequences [11]. Furthermore, online environments may become echo chambers [12] without opposing views [13]. Little is known about whether and how psychological distress is exacerbated when netizens entangle in protest-related discussions in echo chambers.

Collective action and online protest

Activists use social media platforms for discussing and organizing street mass protests [11]. Street protests often are extrapolated onto social media platforms as “online protests” [14]. Online protests can also evolve into street protests [15]. Protesters may perceive contributing to the online discourse can have a constructive impact on accomplishing their goal and contribute to future collective actions [16]. For example, activists in street protests who express their political demands can continue the protest on social media platforms in the form of raising awareness and spreading their message to other social media users, thereby further spreading their influence [17].

Past studies demonstrate the feasibility of detecting protest activities on social media using text mining techniques [7, 18]. For example, a study detected street protests related to the 2016 US presidential election on daily Twitter discussions using terminologies related to social injustice and police violence [7]. Another study analyzing Facebook data in the US and the UK found that increased online engagement on a social network site between opposing political groups was linked with increased offline physical violence [18].

Online materials, such as netizens’ real-time reactions to physical protest events, are important to the study of interactions between collective actions—both online and offline protests—and social media platforms. Online forums, in particular, provided a platform for users to organize and interact with a larger community [11, 19, 20]. During the 2019 social unrest in Hong Kong, two Reddit-like online forums, *Lihkg*.com (*Lihkg*) and Discuss.com.hk (*HKDiscuss*), gained popularity. Similar to

Reddit, users can access most of the content on these forums without creating an account [21]. This affordance is dissimilar to popular social networking sites (SNSs) such as Facebook and Twitter, in which users have the option to limit their content to be visible only to friends. Furthermore, the two online forums have incorporated popular features from SNSs. Users can express their preferences through "likes," similar to Facebook, as well as by using "quoted comments," akin to "retweets" on Twitter [21]. These observations suggest that both *Lihkg* and *HKDiscuss* fall under the broader category of social media platforms, as they incorporate and share similar features with popular social media platforms like Reddit, Facebook, and Twitter.

However, *Lihkg* underwent a subtle change during the 2019 social unrest. Users on *Lihkg* gained the option to make their comments accessible only to other members, which requires having a user account. This feature enables *Lihkg* users to have some control over the visibility of their comments while remaining anonymous. Furthermore, during the 2019 unrest, there was a notable transformation in the primary platforms used for information exchange and communication among activists and their supporters. Telegram and *Lihkg* emerged as the dominant choices, while the utilization of Facebook, Twitter, and WhatsApp declined [22–24]. In addition, according to a poll conducted early on in the 2019 social unrest, 55% of the respondents identified *Lihkg* as the most influential platform in the movement [20, 25]. On the other hand, there is limited investigation on public opinion regarding *HKDiscuss*.

In certain aspects of affordances, both *Lihkg* and *HKDiscuss* deviate from typical SNSs but share similarities with Reddit. Both *forums* lack personalized interfaces for individual users that SNSs might have; instead, these forums function as a large virtual community, much like Reddit [20]. For instance, *Lihkg* incorporates a feature called "most popular lists," which allows users to quickly browse through the most popular user-generated posts on the forum. *Lihkg* also facilitates real-time "voting" among all participated users by determining the inclusion of a post in these "most popular lists" based on the reactions of other users, including the number of comments and upvotes [20]. *HKDiscuss* includes a similar "most popular posts" section. Furthermore, they do not support intentional user tracking or the creation of dedicated spaces for followers to gather [20]. The lack of these features commonly found on other SNSs may encourage individuals on these platforms to engage with other users in the vast online community [20]. However, on *Lihkg*, there is no equivalent to Reddit's karma points that enables users to demonstrate their credibility or popularity [20]. In contrast, on *HKDiscuss*, users have profiles that display information such as "Points," "Membership Level," and "Highlights," which serve as indicators of users' credibility or popularity. This subtle difference may prevent individuals from becoming long-term opinion leadership on *Lihkg*, but not on *HKDiscuss*.

Moreover, both *Lihkg* and *HKDisuss* served as channels for netizens to express their opinions on the protests and share their psychological distress [11]. Using social media platforms, particularly *Lihkg*, anti-government activists create, shape, and promote guiding principles such as the "five demands" and non-ostracization.[1] This

[1] Five demands refer to the five political demands requested by the protesters to the Hong Kong Government during the 2019 anti-extradition bill movement. Non-ostracization refers to a slogan, popular among protesters, of not criticizing other protesters and their protest strategies and tactics.

process was attributed to being the reason behind the high degree of solidarity in the 2019 protests [22]. The degree of solidarity in mass street protests is likely extended to social media platforms as online protests. However, thus far, not much empirical investigation on the reactions of pro-government individuals to the protests has been reported.

Protest and mental health in online political environments

A number of studies have examined the relationship between political attitudes and mental health. A study integrating self-reported survey data, Twitter data, Google search data, and medical data in the US, reveals that liberals were more likely to report depression than conservatives [1]. In Hong Kong, among supporters of the social movement, mental health risk was more severe among those with higher levels of protest participation than those with lower levels [2]. Moreover, people appear to have heightened levels of depressive and sleep symptoms after exposure to social unrest [3, 4], especially those who reported frequent social media use [5]. However, past studies have mainly focused on the general public [3, 4] and the subpopulation of activists and their supporters [1, 2, 5, 26]. Mental health issues of the opposing parties (e.g., anti-protest individuals) have rarely been examined.

Many researchers have underscored the echo chamber effect in explaining the radicalization of political views [12]. The echo chamber effect describes the strengthening of the view held by individuals in the absence of opposing perspectives or information due to the restriction of exposure to the latter [12]. This effect helps explain the polarization of politics in general and views related to COVID-19 in particular [13]. Some argue that the echo chamber effect is particularly salient among extreme partisans [12], while others along the political spectrum may be exposed to relatively more diverse sources of information [12, 27]. Because individuals in an echo chamber may be receiving relatively similar information, including perceived threats from the outgroup, they may have similar emotional reactions (e.g., anger towards the outgroup) as those with a similar political leaning [12, 27]. The latter might be further amplified via a process of mutual validation among similarly minded individuals. This could be a mechanism explaining how user-generated political content of an online environment may contribute to the psychological distress of its users.

Individuals increasingly use social media platforms to discuss and express mental health concerns [28, 29]. Studies were able to detect symptoms of mood disorders, anxiety disorders, and insomnia by analyzing Google Trend data and text mining social media and online forum data [30–37]. To the best of our knowledge, only two studies so far have reported the specific association between collective actions and the expression of emotions using big data. Using ten days of Twitter data and news articles on India's 2012 Nirbhaya protests, Ahmed and colleagues (2017) revealed that expressed positive and negative emotions were congruent to the positive and negative consequences of the protests [1]. Another study, using text mining techniques to analyze six months of social media data during the 2019 social unrest in Hong Kong, found an association between protest events and online discussions of psychological distress on various social media platforms. The study observed time-lagged effects between the variables on online forums, whereas instant messaging on social network sites (SNS) facilitated more immediate conversations [11].

However, evidence of how politically polarized online environments influence individuals' mental well-being remains unclear. Online environments may relay diverse information from other netizens, which may impact readers' mental well-being. Indeed, negative emotions can play a significant role in driving online movements. In Ahmed et al. (2017), online protesters reported a shift from feelings of anxiety and anger to emotional and cognitive liberation [1]. Individuals who support activism may encounter positive or negative emotional information related to both successful and failed collective actions; this information has the potential to impact the mental well-being of its consumers, particularly increasing their anxiety [1]. We propose that individuals in a pro-activist online environment, such as online forums frequented by activists, are more likely to be exposed to emotive content due to the functions of the platform. The sharing of negative emotions among individuals in the same online environment can constitute a form of stressor, potentially contributing to psychological distress.

Taken together, ongoing research shows that activists may react to social unrest by getting involved in collective actions [6, 7, 11, 16, 22, 38], which can entail both offline and online protests [6, 11, 14, 16, 18, 38]. The potential impact of these collective actions on the mental well-being of activists has been explored [1, 2, 5, 26], but there is a significant research gap when it comes to understanding the mental well-being of the opponents. Furthermore, the role of social media platforms in shaping individuals' offline and online protest-related behaviors is crucial, yet the online and offline interactions among activists or among their opponents in these environments remain unclear. It is important to note that individuals within politically polarized online echo chambers may react differently to social unrest, and the discussions related to protests in these environments can contribute to the intensification of affective polarization between the opposing groups [39].

Current study

The current study examined the association between the discussion of protests and psychological distress in politically polarized online environments. We did so by text mining the consecutive day-by-day data from two major online forums during the first six months of the 2019 anti-government social movement in Hong Kong (i.e., June 1 – December 31, 2019). The study is predicated on the notion that a population's involvement on social media platforms reflects the dynamics between collective actions and mental health [11].

We included the data of 183 days during the investigation period from two online forums in Hong Kong, Lihkg.com (*Lihkg*) and Discuss.com.hk (*HKDiscuss*), which are popular with anti-government and pro-government individuals, respectively.[2]

[2] In our other set of analyses focusing specifically on the percentages of anti-government vs. pro-government comments on the two online forums, we found that the vast majority of politically polarized com-

During the 2019 social unrest in Hong Kong, *Lihkg* was one of the two major social media platforms used by activists [38]. *HKDiscuss*, generally favored by those who are pro-government on the other hand has not attracted much empirical investigation.

A previous study [11] identified associations between offline protest events and online user-generated comments containing both protest and psychological distress concepts with the data on various online forums and social network sites. The current study built on it to further the understanding of how online discussions of protests and psychological distress were different in politically polarized (e.g., pro-government vs. anti-government) online environments during the social unrest, we investigated the associations among protest events, comments containing protest concepts, and comments containing psychological distress concepts, on *Lihkg* and *HKDiscuss*. Specifically, we had three hypotheses: (H1) there was a positive association between the percentage of comments containing protest concepts and those containing psychological distress concepts in politically polarized online environments favoring activists (H1a), and a negative association in the environments that favoring their opponents (H1b); (H2) the percentage of comments containing the concepts of interest was positively associated with days with street protests; and (H3) posting of protest-related comments was associated with expressed psychological distress at a later time-point (i.e., time-lagged effects) during the social unrest.

Methods

Dataset

All available comments on the two online forums, *Lihkg* and *HKDiscuss*, were successfully crawled using Python algorithms. However, we cannot obtain the deleted comments on the two online forums, which were deleted by the users or the forum administrators. The percentage of unavailable comments in the overall comments was: 2.95% on *Lihkg* and 27.88% on *HKDiscuss*. The two online forums have different "channels," each relating to a thematic area of discussion, such as politics, news, life, storytelling, etc. The comments from all channels were included, except those from the storytelling channels were excluded due to the high degree of false positives of protest and psychological distress terminologies found.

A total of 39,487,911 online forum comments were included for analyses (*Lihkg* = 31,985,707, and *HKDiscuss* = 7,502,204). Within the study period, there were 75 protest dates and 108 dates without protests. Protest dates were further classified as violent protest dates (k = 48) or non-violent protest dates (k = 27) based on the classification of the South China Morning Post, a major local newspaper published in English [40].

To create variables for statistical analysis, the text data was analyzed using text mining and machine learning analyses. The analyses were performed using the sta-

ments were: 5.28% vs. 0.1% on *Lihkg*, and 0.44% vs. 9.04% on *HKDiscuss*. [masked]. (Under review). *Non-apathetic political neutrality exacerbates the expressions of dehumanization and the acceptance of violence during social unrest: A text mining and machine learning study*. [12]

tistical package SAS 9.4, SAS Text Miner 15.1 [41], and R 3.6.2 [42]. The resulting outcome variables were created by dividing the number of comments that contained either protest concepts, psychological distress concepts, or both (referred to as protest-related psychological distress concepts) by either (1) the total number of comments or (2) the total number of comments that contained protest concepts. Subsequently, we created variables of protest, psychological distress, violent protest dates, and non-violent protest dates. The details of the corpora, text mining and machine learning procedures, and variables are described in Supplementary Material 1.

Corpora and accuracy

Three corpora were created: the protest corpus contained 777 terms, the psychological distress corpus contained 18,239 terms, and the Cantonese corpus contained 7,248 terms. Machine learning training was performed by using Naïve Bayes Classifier with the feature selection function. First, 488 sample comments for protest terms and 150 sample comments for psychological distress terms were randomly selected in all comments. Second, annotation on the sample comments was performed by human raters. Each sample was annotated by two raters. The inter-rater reliabilities indicated satisfied reliability for the annotation (for protest concepts, kappa = 78.65–85.89%; for psychological distress concepts, kappa = 81.56–94.48%). Third, by performing the feature selection function, the machine learning training improved the accuracy of the concepts of interest. The trained accuracies of the text mining results were 93.75% (F1 = 0.95, sensitivity = 0.97, specificity = 0.89) for protest concepts and 82.35% (F1 = 0.75, sensitivity = 0.75, specificity = 0.86) for psychological distress concepts. Table S1 shows the corresponding features (total and selected) of the machine learning training.

Statistical analyses

Time series models, autoregressive integrated moving average with explanatory variable (ARIMAX) [43], were used to analyze the percentages of comments containing the concepts of interest. We treated current online forum data of 183 dates as a time series and defined a period of the season as a week (7 days), with 27 weeks in total. The seasonal effect and the non-stationary effect were addressed before performing the ARIMAX. The following tests and settings of ARIMAX were used [43, 44]: (1) seasonal adjustment was performed to address the seasonality and stationarity. (2) Tests of seasonality and stationarity were then performed to examine whether the time series was non-seasonal and stationary. (3) Test of Akaike information criterion (AIC) was used to assess model fit, a lower AIC indicates a better model fit. We used the auto-selection function to choose the best set of model parameters (p, d, q) according to the lowest AIC value for each ARIMAX model. (4) Ljung–Box test was performed to test if the group of autocorrelations was not different from zero (i.e., retain the null) for each model.

Three data frames were used in the analyses for examining H1a and H1b. The percentage of comments with protest concepts (data frame 1), psychological distress concepts (data frame 2), and both protest and psychological distress concepts (data frame 3) were treated as the outcome variable in each model. Three crude models were separately analyzed for data frames 1–3, and two adjusted models were separately analyzed for data frames 2 and 3. All models were performed separately for the data from *Lihkg* and *HKDiscuss*, which resulted in 6 crude models and 4 adjusted models in total.

For examining H2, in crude models 1 and 4, protest dates and non-protest dates were the exogenous variables. In crude models 2 and 5, the dummy variables "violent protest dates" and "non-protest dates" were the exogenous variables. In crude models 3 and 6, the percentage of comments with protest concepts was the exogenous variable.

In all the adjusted models, protest dates and non-protest dates and the percentage of comments with protest concepts were the exogenous variables. In the adjusted models 1 and 3, we controlled for the interaction of the percentage of comments with protest concepts and protest dates (protest vs. non-protest). In the adjusted models 2 and 4, we controlled for the interaction of the percentage of comments with protest concepts and protest dates (dummy coded: violent protest dates vs. other dates; non-protest dates vs. other dates). In addition, we have investigated the time-lagged effects in all the models mentioned above (H3).

The statistical package R 3.6.2 [42] was used for the statistical analyses. The significance level was set at $p < 0.05$ and the confidence level was set at 95%.

Results

Daily percentages of comments on protest and psychological distress

Figures S1–4 present the day-by-day trends of the percentages of comments containing protest- and psychological distress-related concepts on *Lihkg* and *HKDiscuss*. Table S2 shows the means and percentages of the number of comments containing each investigated concept.

The percentages of comments that included protest concepts on both online forums increased from June to early August, and then decreased until early November; these percentages were higher on *HKDiscuss* than on *Lihkg* on most of the dates (Figure S1). These percentages on both online forums were higher on protest dates (especially on violent protest dates) than on non-protest dates (Table S2).

The percentages of comments that included psychological distress concepts on *Lihkg* increased from (1) June to mid of August and (2) from late August to late October; the corresponding percentages on *HKDiscuss* were relatively steady throughout the dates (Figure S2). These percentages on both online forums were slightly lower on protest dates (especially on violent protest dates) than on non-protest dates (Table S2).

The percentages of comments that included both protest and psychological distress concepts among all comments on both online forums increased from June to mid-August and then became steady until the end of November except on a few particular dates from September to November. These percentages were higher on *Lihkg* than on *HKDiscuss* on most of the dates (Figure S3). These percentages on both online forums were slightly higher on protest dates (especially on violent protest dates for *Lihkg*) than on non-protest dates; however, the percentages on *HKDiscuss* were lower on violent protest dates than on non-protest dates (Table S2). The percentages of comments that included both protest concepts and psychological distress concepts among protest comments on *Lihkg* increased from June to mid-August and then became steady until the end of November except on a few particular dates in September and October. These percentages on *HKDiscuss* were relatively steady throughout the dates. These percentages were higher on *Lihkg* than on *HKDiscuss* on most of the dates (Figure S4). These percentages on both online forums were lower on protest dates (especially on violent protest dates) than on non-protest dates (Table S2).

Time-series analyses

All time-series models (ARIMAX) were adjusted for seasonality and stationarity; these systematic effects were eliminated. Subsequently, the time series became non-seasonal and stationary (i.e. the variance remained constant). The Ljung–Box tests of each model were not significant, suggesting that the models were good fits to the data. Table 1 presents the results of the ARIMAX models of the data from the two online forums. In the crude models for the data from both forums, the percentage of comments with protest concepts was not significantly associated with protest dates or violent protest dates.

Psychological distress and protests. In both crude and adjusted models for *Lihkg* data, the percentage of comments with psychological distress concepts was positively associated with the percentage of comments with protest concepts (Crude model 3: estimate = 0.032; 95% CI, 0.020–0.044; $p < 0.001$. Adjusted model 1: estimate = 0.032; 95% CI, 0.019–0.046; $p < 0.001$. Adjusted model 2: estimate = 0.034; 95% CI, 0.010–0.058; $p = 0.005$). However, the percentage of comments with psychological distress concepts among all comments was not associated with protest dates or violent protest dates. In the crude model for *HKDiscuss* data, the percentage of comments with psychological distress concepts was relatively lower on violent protest dates than on other dates (Crude model 5: estimate < -0.001; 95% CI, < -0.001 – < -0.001; $p = 0.029$). However, the percentage of comments with psychological distress concepts among all comments was not associated with protest dates nor the percentage of comments with protest concepts. All adjusted models were not significant.

Protest-related psychological distress and protests. In both crude and adjusted models for *Lihkg* data, the percentage of comments with protest-related psychological distress concepts among all comments was positively associated with the percentage of comments with protest concepts (Crude model 3: estimate = 0.027; 95% CI, 0.019–0.034; $p < 0.001$. Adjusted model 1: estimate = 0.027; 95% CI, 0.019–0.035; $p < 0.001$. Adjusted model 2: estimate = 0.033; 95% CI, 0.017–0.048; $p < 0.001$). However, the percentage of comments with protest-related psychological distress concepts among protest comments was not significantly associated with the percentage of comments with protest concepts. The results indicate that netizens on *Lihkg* had expressed mental health concerns regardless of whether they had mentioned the protest (H1a).

Table 1 Time-series analyses of percentages of comments during 1 June – 30 November 2019

	Protest concepts				Psychological distress concepts			
	Parameter	Estimate	95% CI	*p*	Parameter	Estimate	95% CI	*p*
Lihkg								
Crude model 1	(1,0,0)(0,0,0)				(1,0,1)(0,0,0)			
Protest dates		< 0.001	-0.002–0.004	0.587		< -0.001	< -0.001 – < 0.001	0.675
Crude model 2	(2,0,1)(0,0,0)				(1,0,1)(0,0,0)			
Violent protest dates		0.002	-0.003–0.007	0.412		< 0.001	< -0.001 – < 0.001	0.908
Non-protest dates		< 0.001	-0.004–0.004	0.968		< 0.001	< -0.001 – < 0.001	0.689
Crude model 3		NA			(1,0,1)(0,0,0)			
Protest concepts						0.032	0.020–0.044	< 0.001***
Adjusted model 1		NA			(1,0,1)(0,0,0)			
Protest dates						< -0.001	< -0.001 – < 0.001	0.457
Protest concepts						0.032	0.019–0.046	< 0.001***
Adjusted model 2		NA			(1,0,1)(0,0,0)			
Violent protest dates						< -0.001	< -0.001 – < 0.001	0.916

Table 1 (continued)

	Protest concepts				Psychological distress concepts			
	Parameter	Estimate	95% CI	*p*	Parameter	Estimate	95% CI	*p*
Non-protest dates						< 0.001	< -0.001 – < 0.001	0.633
Protest concepts						0.034	0.010–0.058	0.005**
HK-Discuss								
Crude model 4	(1,0,0)(0,0,0)				(1,0,1)(0,0,0)			
Protest dates		0.001	-0.002–0.005	0.388		< -0.001	< -0.001 – < 0.001	0.160
Crude model 5	(1,0,0)(0,0,0)				(1,0,0)(0,0,0)			
Violent protest dates		0.003	-0.002–0.007	0.232		< -0.001	< -0.001 – < -0.001	0.029*
Non-protest dates		< 0.001	-0.004–0.004	0.968		< -0.001	< -0.001 – < 0.001	0.794
Crude model 6		NA			(1,0,1)(0,0,0)			
Protest concepts						0.002	-0.003–0.007	0.480
Adjusted model 3		NA			(2,0,2)(0,0,0)			
Protest dates						< -0.001	< -0.001 – < 0.001	0.132
Protest concepts						0.004	-0.002–0.011	0.186

Table 1 (continued)

	Protest concepts				Psychological distress concepts			
	Parameter	Estimate	95% CI	*p*	Parameter	Estimate	95% CI	*p*
Adjusted model 4		NA			(2,0,2) (0,0,0)			
Violent protest dates						< -0.001	< -0.001 – < 0.001	0.057
Non-protest dates						< -0.001	< -0.001 – < 0.001	0.941
Protest concepts						0.002	-0.008–0.012	0.735

Note These are results from the autoregressive integrated moving average with explanatory variable models (ARIMAX). Parameter for time-series (p, d, q) and seasonality (P, D, Q). Crude models 1 and 4, and adjusted models 1 and 3, included "non-protest dates" as the reference group. Crude models 2 and 5, and adjusted models 2 and 4, included dummy variables of "violent protest dates" and "non-protest dates"; and "other dates" as the reference group. In the adjusted models 1 and 3, we controlled for the interaction of percentage of protest concepts and protest dates (protest vs. non-protest). In the adjusted models 2 and 4, we controlled for the interaction of percentage of protest concepts and protest dates (dummy coded: violent protest dates vs. other dates; non-protest dates vs. other dates)

In both crude and adjusted models for *HKDiscuss* data, the percentage of comments with protest-related psychological distress concepts among all comments was positively associated with the percentage of comments with protest concepts (Crude model 6: estimate=0.007; 95% CI, 0.005–0.010; $p<0.001$. Adjusted model 3: estimate=0.009; 95% CI, 0.005–0.012; $p<0.001$. Adjusted model 4: estimate=0.008; 95% CI, 0.002–0.013; $p=0.008$). The percentage of comments with protest-related psychological distress concepts among protest comments was negatively associated with the percentage of comments with protest concepts (Crude model 6: estimate = -0.122; 95% CI, -0.162 – -0.082; $p<0.001$. Adjusted model 3: estimate = -0.128; 95% CI, -0.178 – -0.078; $p<0.001$. Adjusted model 4: estimate = -0.099; 95% CI, -0.175 – -0.023; $p=0.011$) (H1b). In both crude and adjusted models for *HKDiscuss* data, the percentage of comments with protest-related psychological distress concepts among comments with protest concepts was relatively lower on protest dates than on non-protest dates (Crude model 4: estimate = -0.002; 95% CI, -0.003 – < -0.001; $p=0.017$. Adjusted model 3: estimate = -0.002; 95% CI, -0.003 – < -0.001; $p=0.031$), and lower on violent protest dates than on other dates (Crude model 5: estimate = -0.003; 95% CI, -0.006 – -0.001; $p=0.003$. Adjusted model 4: estimate = -0.004; 95% CI, -0.006 – -0.001; $p<0.001$). However, these associations were not significant in the percentage of comments with protest-related psychological distress concepts among all comments. These results in the comments with protest concepts on *HKDiscuss* indicate that when people were discussing the protests, they had fewer reports of protest-related psychological distress on the protest dates, especially on violent protest dates (H2).

Time-dependence. Time-lagged effects were found in all significant models (i.e. the value of the parameter p is greater than 0), which suggests that the discussions of protests and the reports of psychological distress continued on the days following the protests on both online forums (H3) (See Table 2).

Discussion

This study examined six-month worth of online forum data during the 2019 social unrest in Hong Kong. The results suggest that more discussions on the protests were simultaneously associated with more mentions of psychological distress on both *Lihkg* (Crude model 3, and adjusted models 1 and 2; H1a) and *HKDiscuss* (Crude model 6, and adjusted models 3 and 4; H1b), and these associations continued on the subsequent days (H3). Contrary to H2, the *relative* amount of discussions on the protests and mention of psychological distress among user of *Lihkg* were not different between days with protests and days without, which indicates that these discussions were not influenced by the occurrence of protests during the protest dates. In addition, users of *HKDiscuss* had fewer mentions of psychological distress on the protest dates (especially on violent protest dates) than on non-protest dates. Both prior studies and our own data suggest *Lihkg* is generally perceived as a platform popular among those who are more anti-government, whereas *HKDiscuss* is perceived as a platform that is relatively more popular among those who are pro-government.[3] Our results add evidence to the potential association between political polarity (anti- vs. pro-government) and protest-related psychological distress. Taken together, similar to results from self-report data, exposure to the social unrest and the discussions on social media and online forums may have influenced on the psychological well-being [45] and mental health symptoms [3] of their users.

Offline street protests and online activities have a time-dependent association

The time-lagged effects in the time-series results indicate that netizens continued to discuss protests and mention protest-related psychological distress on the days following the offline protest events. Consistent with a previous study [11], our data also show that the occurrence of street protests was synchronized with the online discussion of the protests. The street protests may also continue as online protests in the subsequent days, suggesting a mutual and dynamic influence between the street and online protests.

[3] Percentages of anti-government vs. pro-government comments on the two online forums were: 5.28% vs. 0.1% on *Lihkg*, and 0.44% vs. 9.04% on *HKDiscuss*.

Table 2 Time-series analyses of percentages of comments during 1 June – 30 November 2019

	Protest-related psychological distress concepts among all comments				Protest-related psychological distress concepts among protest comments			
	Parameter	Estimate	95% CI	*p*	Parameter	Estimate	95% CI	*p*
Lihkg								
Crude model 1	(1,0,1) (0,0,0)				(2,0,1) (0,0,0)			
Protest dates		< -0.001	< -0.001 – < 0.001	0.725		-0.002	-0.006–0.002	0.248
Crude model 2	(1,0,1) (0,0,0)				(2,0,1) (0,0,0)			
Violent protest dates		<0.001	< -0.001 – < 0.001	0.510		<0.001	-0.005–0.006	0.783
Non-protest dates		<0.001	< -0.001 – < 0.001	0.474		0.003	-0.002–0.007	0.292
Crude model 3	(1,0,1) (0,0,0)				(1,0,2) (0,0,0)			
Protest concepts		0.027	0.019–0.034	<0.001***		-0.006	-0.132–0.120	0.928
Adjusted model 1	(1,0,1) (0,0,0)				(1,0,2) (0,0,0)			
Protest dates		< -0.001	< -0.001 – < 0.001	0.305		-0.002	-0.006–0.001	0.226
Protest concepts		0.027	0.019–0.035	<0.001***		-0.019	-0.156–0.118	0.787
Adjusted model 2	(1,0,1) (0,0,0)				(2,0,1) (0,0,0)			
Violent protest dates		<0.001	< -0.001 – < 0.001	0.749		<0.001	-0.005–0.006	0.855

Table 2 (continued)

	Protest-related psychological distress concepts among all comments				Protest-related psychological distress concepts among protest comments			
	Parameter	Estimate	95% CI	p	Parameter	Estimate	95% CI	p
Non-protest dates		< 0.001	< -0.001 – < 0.001	0.337		0.003	-0.002–0.007	0.296
Protest concepts		0.033	0.017–0.048	< 0.001***		0.046	-0.203–0.295	0.717
HK-Discuss								
Crude model 4	(1,0,1) (0,0,0)				(2,0,0) (0,0,0)			
Protest dates		< -0.001	< -0.001 – < 0.001	0.581		-0.002	-0.003 – < -0.001	0.017*
Crude model 5	(1,0,1) (0,0,0)				(2,0,0) (0,0,0)			
Violent protest dates		< -0.001	< -0.001 – < 0.001	0.194		-0.003	-0.006 – -0.001	0.003**
Non-protest dates		< -0.001	< -0.001 – < 0.001	0.727		< 0.001	-0.002–0.002	0.997
Crude model 6	(1,0,1) (0,0,0)				(1,0,0) (0,0,0)			
Protest concepts		0.007	0.005–0.010	< 0.001***		-0.122	-0.162 – -0.082	< 0.001***
Adjusted model 3	(1,0,1) (0,0,0)				(1,0,0) (0,0,0)			
Protest dates		< -0.001	< -0.001 – < 0.001	0.445		-0.002	-0.003 – < -0.001	0.031*
Protest concepts		0.009	0.005–0.012	< 0.001***		-0.128	-0.178 – -0.078	< 0.001***

Table 2 (continued)

	Protest-related psychological distress concepts among all comments				Protest-related psychological distress concepts among protest comments			
	Parameter	Estimate	95% CI	*p*	Parameter	Estimate	95% CI	*p*
Adjusted model 4	(1,0,1) (0,0,0)				(1,0,0) (0,0,0)			
Violent protest dates		< -0.001	< -0.001 – < 0.001	0.075		-0.004	-0.006 – -0.001	0.001**
Non-protest dates		< -0.001	< -0.001 – < 0.001	0.622		< -0.001	-0.002–0.002	0.760
Protest concepts		0.008	0.002–0.013	0.008**		-0.099	-0.175 – -0.023	0.011*

Note These are results from the autoregressive integrated moving average with explanatory variable models (ARIMAX). Parameter for time-series (p, d, q) and seasonality (P, D, Q). Crude models 1 and 4, and adjusted models 1 and 3, included "non-protest dates" as the reference group. Crude models 2 and 5, and adjusted models 2 and 4, included dummy variables of "violent protest dates" and "non-protest dates"; and "other dates" as the reference group. In the adjusted models 1 and 3, we controlled for the interaction of percentage of protest concepts and protest dates (protest vs. non-protest). In the adjusted models 2 and 4, we controlled for the interaction of percentage of protest concepts and protest dates (dummy coded: violent protest dates vs. other dates; non-protest dates vs. other dates)

Psychological distress may be moderated by political differences

Evidence suggests a significant increase in mental health issues among Hong Kong people during the 2019 anti-government social movement [4]. Our study extends the evidence from street protest activities to online protest activities on politically polarized online forums. The dynamics between protests and psychological distress were time-dependent; individuals' real-time, online, affectively-loaded reactions continued after the street protests.

A previous study [11] revealed the prevalence of protest-related psychological distress on social media platforms. We extend the evidence that individuals' reactions were different on *Lihkg* and *HKDiscuss*. On *HKDiscuss* but not on *Lihkg*, the percentage of comments with psychological distress concepts was relatively lower on days with protest than days without, especially on days with violent protest. The social unrest was predominantly an anti-government social movement [46]. Activists may seek support and foster solidarity by promoting and discussing the protests on social media platforms, especially *Lihkg* [22]. Street protests may be continued on social media platforms as online protests [14], especially platforms that are predominantly used by activists and their supporters. These online protests are less likely to take place on platforms that are primarily used by the movement's opponents (e.g., *HKDiscuss*). We found that the discussions of protest and the related psychological distress were not different between days with protest and days without on *Lihkg*, but were relatively lower on days with protest than days without on *HKDiscuss*. This could be attributed to the frequent dispersal of activists by the police during the violent protest dates, effectively curbing the violent conflicts between activists and the police. Some of these pro-government forum users may even be encouraged by the might exhibited by the police force against their outgroup. Some opponents may perceive less distress due to the resolution of these confrontations. However, the current study did not investigate individuals' perception of the conflicts and the dispersal per se. Future research can examine the underlying association between the characteristics of specific events and individuals' psychological responses. For example, it would be valuable to investigate how individuals perceive the severity of a protest or scale of conflict. Some may consider large dispersals as those that involve a large number of participants from both anti-government and pro-government sides, while others may consider large dispersals as those that are characterized by a high level of violent conflicts between the activists and the police. Furthermore, exploring the potential association between perceived large or small dispersal and levels of psychological distress expressed online could provide further evidence to support this argument.

The found association between protest and mental health discourse is consistent with self-reporting data that showed that online exposure to protest-related information may worsen depressive symptoms [47]. Our findings regarding the differences between *Lihkg* and *HKDiscuss* suggest that the mention of protest-related psychological distress was lower among those who were pro-government than those who were anti-government. Furthermore, for those who were pro-government, the mention of protest-related psychological distress was relatively lower on days with protest than days without. These findings suggest a potential association between protest-related psychological distress and political polarity, in which anti-government street protests had less psychological impact on those who are pro-government than on those who are anti-government.

Protest-related psychological distress in politically polarized online environments

A previous study investigated political polarization in online echo chambers [13], but, to the best of our knowledge, the current one is the first study of politically polarized social media platforms that examined the influence of collective actions on mental health. The two online forums included in this study have been characterized as echo chambers for anti-government (i.e., those on *Lihkg*) and pro-government netizens (i.e., those on *HKDiscuss*).[2]

When engaging in discussions on online forums, netizens typically interact with a greater number of people than they would offline. They may be exposed to a large amount of negatively valence online content, such as expressions of stress, anger, and helplessness. As reviewed above, in the subpopulation of pro-democracy supporters, those with higher levels of protest participation were found to have a heightened risk of mental health than those with lower levels [2]. The current study further shows that online protest discussion and expression of psychological distress on online forums likely differ between opposition groups along the political spectrum.

The presence of common features such as "likes" and "retweets" on the two online forums and popular social media platforms such as Facebook, Twitter, and Reddit [21] align both *Lihkg* and *HKDiscuss* with a broader category of social media platforms. However, on *Lihkg* there is a lack of features that allows users to *follow* other users [20]. This is similar on *HKDiscuss*. This absence of a follow function may contribute to the participation of individuals in the large virtual community [20], where users engaged in collective discussions related to the protests and expressed psychological distress facing a larger audience. Although *HKDiscuss* offers a similar feature, our results indicate that such discussions and expressions were relatively fewer on protest days compared to days without. This suggests that echo chambers—e.g., environments that are dominated by relatively homogenous comments favoring one view—influence the discussions and expressions among participating users in different ways. However, this association would require further empirical verification.

The findings obtained from these forums can potentially be extrapolated to political discussions on other echo chambers, such as those found on Twitter [13]. Further investigation into echo chambers with different affordances is warranted. For example, whether and how the functionalities and user-created environments shape the naturally occurring behaviors of users, such as the discussion of protests and the expression of psychological distress. Echo chambers may have a detrimental impact on those in them. An online environment where a particular political leaning dominates (e.g., dominant anti-government leaning on *Lihkg* and pro-government leaning on *HKDiscuss*), the absence of opposing view [13] may further increases netizens' exposure to stress and distress expressed by fellow members with similar political attitudes and affinity. Netizens in an echo chamber would also likely experience more stressors online, such as the day-by-day discussions derived from street protests, which in turn could impose a greater risk of mental health problems [5, 48].

Another function that echo chambers potentially serve, by which they may further gain in popularity, is the cultivation of perceived social support. In general, a stronger social connection may buffer the adverse impact of the stress triggered or exacerbated by collective actions, no matter which side the person may be on along the political spectrum [5, 49–51]. The current results on *HKDiscuss* show a potential reduction of protest-related psychological distress when individuals discuss the protest-related topics in an opponents' echo chamber.

Perceived social connection or shared ingroup identity in politically polarized echo chambers may buffer the online adverse experience, such as mental health concerns, in a stressful environment or a stress exposure derived from protest discussions. We argue that people who are socially connected or have stronger identification with the ingroup may more likely share in common the psychological distress of other netizens. In other words, online discussions under an echo chamber may increase shared stress exposure from people with similar viewpoints. Repeated exposure of collective distress may further exacerbate individual psychological distress. More study on this possible mechanism is needed.

Individuals with higher levels of protest participation were found to have a greater risk of mental health issues compared to those with lower levels of participation [2].

Netizens in an anti-government environment may participate in the social movement through online means, which may exert on them protest-related stressors. This experience may induce psychological distress and thus the expression of mental health concerns. In contrast, when pro-government netizens in a pro-government environment are exposed to adverse content, such as discussions about political conflicts between activists and the police, does not necessarily result in their participation in anti-government online protests. They may only express mental health concerns whilst having discussions about violent street conflicts between protesters and police or anti-protesters. These differences between the echo chambers may reflect and elicit differing reactions toward the offline conflicts among users of the pro-government and anti-government online forums.

Further study may examine how affordance impacts mental health in echo chambers, and how people may respond to and react in the online environment of the other side of the political spectrum, e.g., anti-government activists on pro-government online forums, and vice versa. Moreover, conducting research on the disparities between the forums examined in the study, which were influential online echo chambers during the 2019 social unrest, and popular social media platforms such as Facebook, Twitter, and Reddit would facilitate the integration of the current findings with the larger literature, including that of computer-mediated communication. This investigation would enable a deeper understanding of the distinct attributes and impacts associated with various online platforms during episodes of social unrest.

Limitations

This study has several limitations. We cannot ascertain that our datasets contain 100% of the posts from *Lihkg* and *HKDiscuss* since some of the posts might have been deleted by the post owners or the forum administrators before our data collection. Second, we only included two online forums, albeit the most popular ones at the time of the 2019 social unrest.[4] Whether or not the findings are generalizable to those who do not use these platforms is yet to be determined. Third, we cannot (and do not) assume the mention of psychological distress equals suffering from a mental disorder. Relatedly, the accuracy and F-1 score of the concept of psychological distress were 82% and 75%, respectively. Future studies should try to improve the accuracy in order to improve the operationalization and measurement of the construct. Furthermore, we did not measure semantic differences and different sentiments of words the netizens used to express psychological distress. Instead, we used the discussion of such symptoms as a proxy of distress and focused on the fluctuation over time, which we maintain is both theoretically meaningful and practically useful. Fourth, our current time-series analysis cannot determine whether the same set of netizens were posting messages on protest dates compared to non-protest dates. We treated the data on the online forum as a collective representation of netizens. In future studies,

[4] We used Meltwater Database [52]. Meltwater News Hong Kong Ltd. (2019). Meltwater Database. In. Hong Kong. to identify protests-related comments on online forums in Hong Kong during the study period (June and Novemember 2019). The most prevalent numbers of protest-related comments were found on *Lihkg* and *HKDiscuss*.

it is suggested to examine individual-level variation across time, e.g., their posting behaviors during the protest versus non-protest dates.

Conclusion

Social movement and the accompanying mass protests are increasingly common. Their potential impact on public health deserves attention. The current study demonstrates the possibility of using text mining and machine learning techniques to reveal the dynamics between social unrest and its psychological sequelae using day-by-day online forum data. We revealed the real-time reactions of online forum users to the protests and their protest-related psychological distress. Delivery of information and discussions of current social unrest are rapid on social media platforms. The monitoring of online forum content is a viable and cost-effective way to understand the real-time public opinion on critical events and their potential impact on mental health. This study extends evidence to reveal not only online users in an anti-government environment but also those in a pro-government environment may have mental health concerns, albeit to a lesser extent, during the 2019 social unrest. The echo chamber effect could potentially play a role; people in different echo chambers may experience different means of affordance and content of discussions, which may have impacted their expression of mental health concerns. Policymakers can consider utilizing online forum data to investigate public opinions concerning social and political issues and their mental health consequences, with the hope to mitigate or prevent largescale mental health crises.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s42001-024-00274-7.

Data availability The text data were taken from publicly accessible websites Lihkg.com and Discuss.com.hk. The corresponding author will determine the suitability of sharing the crawled data based on the intended purpose of its use.

Declarations

Conflict of interest The authors have no competing interests.

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