scientific reports

OPEN

Predicting public mental health needs in a crisis using social media indicators: a Singapore big data study

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Mental health issues have increased substantially since the onset of the COVID-19 pandemic. However, health policymakers do not have adequate data and tools to predict mental health demand, especially amid a crisis. Using time-series data collected in Singapore, this study examines if and how algorithmically measured emotion indicators from Twitter posts can help forecast emergency mental health needs. We measured the mental health needs during 549 days from 1 July 2020 to 31 December 2021 using the public's daily visits to the emergency room of the country's largest psychiatric hospital and the number of users with "crisis" state assessed through a government-initiated online mental health self-help portal. Pairwise Granger-causality tests covering lag length from 1 day to 5 days indicated that forecast models using Twitter joy, anger and sadness emotions as predictors perform significantly better than baseline models using past mental health needs data alone (e.g., Joy Intensity on IMH Visits, $\chi2 = 14{\cdot}9$, $P < {\cdot}001$*; Sadness Count on Mindline Crisis, $\chi2 = 4{\cdot}6$, $P = {\cdot}031$*, with a one-day lag length). The findings highlight the potential of new early indicators for tracking emerging public mental health needs.**

Keywords Mental health, Social media, Emotions, Forecasting, COVID-19, Public health

Governments and studies worldwide have reported a significant increase in mental health issues associated with the impact of the COVID-19 pandemic[1–4]. Globally, the cases of major depressive disorder have been estimated to increase by 53·2 million cases, and anxiety to increase by 76·2 million[5]. Mental health during the early days of COVID-19 was closely related to the social restrictions imposed, where depression symptoms significantly increased when social restrictions were tightened[6]. Furthermore, poorer mental well-being was found among individuals with lower collectivism and higher social media use during COVID-19[7].

In a disease outbreak such as the COVID-19 crisis, situations can change in hours, if not within a day. However, to date, health policymakers do not have adequate tools to anticipate or predict mental healthcare needs, which would allow the pre-allocation of resources or the calibration of policy to meet these needs. Singapore, a city-state with a total population of 5.68 million[8], reported 452 suicides in 2020, a record high since 2012[9]. During the "Circuit Breaker" period between 7 April to 1 June 2020, when Singapore implemented the most stringent measures to control the community spread of COVID-19, more than 6,600 calls were made to the 24-hour National Care Hotline, with callers covering topics such as government support measures, family conflicts, financial issues, and anxiety[10]. Resources were in short supply to address such emergency demands for mental healthcare.

Conventional survey methods suffer from limitations in timeliness because their results are based on responses collected at a single point in time, which provides only a snapshot of the situation and often lags in reporting insights a few months after the actual situation. Social media platforms such as Twitter (now rebranded as "X"; we used the original name based on the time we collected the data) continuously generate data

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on people's thoughts and feelings that are publicly accessible. However, the challenges of using social media data for surveillance and forecasts are associated with high sparsity and low signal-to-noise ratio issues that require effective extraction of useful information. Previous studies have found, for example, that the count of particular words extracted from Facebook posts of individuals can be used as a predictor of these individuals' likelihood of depression diagnosis in the future[11]. Despite recent studies[12,13] that examine the predictive value of the temporal duration, the prediction problem for mental health in the context of a pandemic remains unstudied.

Emotions are a key driver of human behaviours, and the onset and intensity of emotions are sensitive to situational changes[14,15]. Compared to broad situations, emotions are likely to be more effective predictors preceding the downstream emergence of mental health conditions and related care-seeking behaviours. To our knowledge, no studies have quantitatively examined the predictive value of the fine-grained emotions expressed from social media platforms and the degree to which these emotions can provide early indications of downstream mental healthcare needs and demands.

This study contributes to the need for more effective data and tools in addressing public mental health problems, especially during a crisis[16,17]. The key objective of our study is to explore how fine-grained social media emotions can enhance the prediction of the change in mental healthcare needs and demands. We focus on the following two research questions:

RQ1: Will the changes in situation indicators and emotions expressed from social media platforms, namely fear, anger, joy, and sadness, enhance the prediction of the public's mental healthcare needs? Are the emotion indicators more useful than situation indicators?

RQ2: If the enhancement effects from the new emotion predictors exist, how can the enhanced models possibly help forecast near-term mental health needs change?

To address the research questions, we collected data from different sources. We extracted three groups of variables, namely (a) mental health needs as outcome variables, (b) emotions expressed in social media (Twitter in this study) posts as main predictor variables, and (c) indicators surrounding the severity of the COVID-19 situations as comparative predictor variables (the standard pandemic indicators used by health authorities). We sought and obtained access to data on public visits to the emergency room of the country's largest psychiatric hospital, the Institute of Mental Health (IMH), as a primary proxy for the public's emergency mental healthcare needs. At the same time, as more people turn to seek help online, we collected data from mindline.sg, a government-initiated mental health help online portal (hereafter Mindline), which has features to measure anonymous responses to depression and general anxiety order tests. We employed pairwise Granger-causality analysis and auto-regressive integrated moving average (ARIMA) forecasting model analysis for the statistical tests.

Results

Between 1 July 2020 and 31 December 2021, spanning 549 days, 31,905 individuals sought help from IMH's emergency room services, averaging 58 visits a day. 23,648 individuals completed the mental health status self-assessment questionnaire on Mindline, and 7,901 of them had a "Crisis" status (Fig. 1). During this period, 140,598 unique tweets were posted to Twitter. There were 235,400 COVID-19 cases and 801 deaths reported,

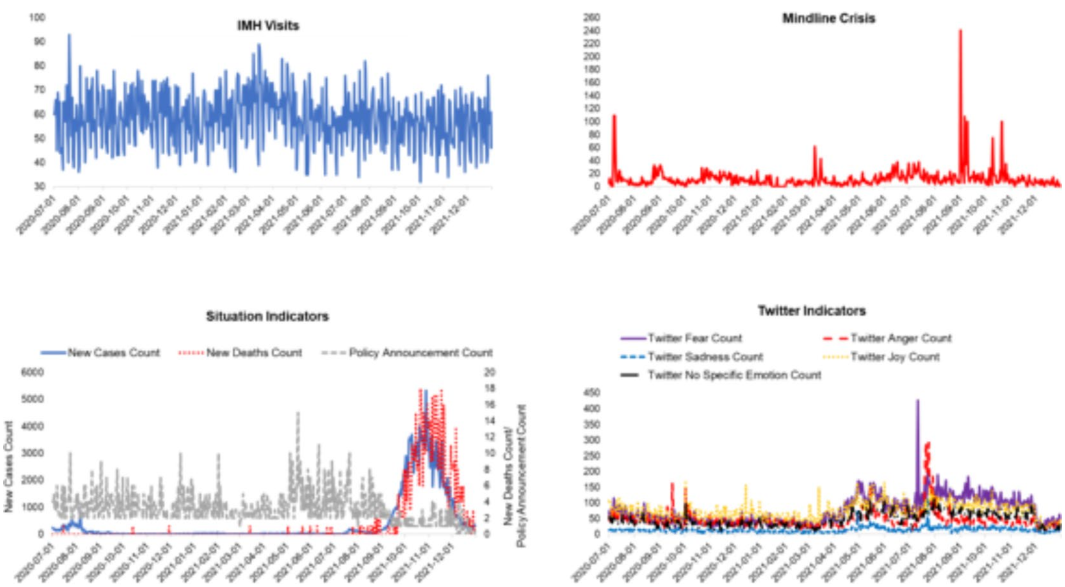

Fig. 1. The overall trends of the data streams collected for this study. The visits to the emergency room of IMH, use of the self-help online portal mindline.sg, situation indicators, and Twitter indicators over the study period are shown in actual values to illustrate the overall trends of changes. Normalisation of the data has been performed for subsequent forecasting tests.

Granger causality tests with significant links	Lag length (days)	χ2	*P*-value
Predicting IHM Visits – Public visits to the emergency department of IMH			
Joy Intensity ↛ IMH Visits	1	14·9	<·001***
Announcement Count ↛ IMH Visits	2	8·6	·014*
Tweet Count ↛ IMH Visits	2	7·6	·023*
New Cases Count ↛ IMH Visits	3	10·3	·016*
Anger Count ↛ IMH Visits	4	10·1	·038*
Predicting Mindline Crisis - New users who visited mindline.sg and were assessed in "Crisis" status			
Sadness Count ↛ Mindline Crisis	1	4·6	·031*
Joy Intensity ↛ Mindline Crisis	1	4·1	·042*
Anger Count ↛ Mindline Crisis	1	3·9	·049*
Tweet Count ↛ Mindline Crisis	3	8·5	·036*
Joy Count ↛ Mindline Crisis	5	19·6	·002**

Table 1. Granger causality results of daily COVID-19 Twitter emotions and situation indicators significantly predict changes in IMH visits and Mindline Crisis status. Test results are sorted in the increasing order of lag length (days).

Model no.	ARIMA model [lag day]	Model prediction error	
		RMSE	MAE
1	IMH Visits [1]	6·95	5·71
2	IMH Visits + Joy Intensity [1]	7·02	5·80
3	IMH Visits [2]	7·64	5·47
4	IMH Visits + Announcement Count [2]	7·62	5·51
5	**IMH Visits + Tweet Count [2]**	**6·83**	**5·74**
6	IMH Visits [3]	18·49	16·69
7	IMH Visits + New Cases [3]	7·25	6·06
8	IMH Visits [4]	9·83	7·62
9	IMH Visits + Anger Count [4]	9·91	7·70

Table 2. Error scores for each ARIMA model with and without additional χ variable in modelling IMH visits (results are sorted based on lowest to highest RMSE scores; lower RMSE indicates better models).

according to records from World Health Organization (WHO). Singapore's Ministry of Health (MOH) issued 1,748 announcements related to COVID-19 development and policies to manage the pandemic.

Predictive effects of Twitter indicators and situation indicators on mental health needs

In addressing our primary research question, pairwise Granger-causality tests showed that some emotion-related indicators extracted from Twitter were useful in predicting *IMH Visits* and *Mindline Crisis* trends, with a lag-length range from one to five lag days (Table 1).

Twitter's joy and anger-related indicators had significant Granger-causality effects when predicting IMH Visits. *Joy Intensity* Granger-caused *IMH Visits* with one lag day (χ2 = 14·9, P < ·001***). *Anger Count* Granger-caused *IMH Visits* with four lag days (χ2 = 10·1, P = ·038*). The count of daily number of tweets, *Tweet Count* Granger-caused *IMH Visits* with two lag days (χ2 = 7·6, P = ·023*).

Four emotion indicators were found to provide forecasting value for predicting the self-assessed critical mental status variables measured by *Mindline Crisis*. These indicators include *Joy Count* (χ2 = 19·6, P = ·0015**), *Sadness Count* (χ2 = 4·6, P = ·031*), *Joy Intensity* (χ2 = 4·1, P = ·0042**) and *Anger Count* (χ2 = 3·9, P = ·049*). *Tweet Count* Granger-caused Mindline Crisis with three lag days (χ2 = 8·5, P = ·036*).

As a comparison, pairwise tests performed on different situation indicators showed that none of the situation indicators significantly predicted *Mindline Crisis*, and only two situation indicators had Granger-causality effects in predicting *IMH Visits*. *New Cases Count* Granger-caused *IMH Visits* with three lag days (χ2 = 10·3, *P* = ·016*), and *Announcement Count* Granger-caused *IMH Visits* with two lag days (χ2 = 8·6, *P* = ·014*). The other three situation indicators, i.e., *Cumulative Cases Count*, *New Deaths Count*, and *Cumulative Deaths Count*, did not present significant Granger-causality effects in predicting *IMH Visits*.

ARIMA model comparison results

IMH Visits. Table 2 presents the error values for each ARIMA model with and without the additional lagged values of *X* in predicting *IMH Visits* as *Y*, based on the modelling parameter we configured to simulate the

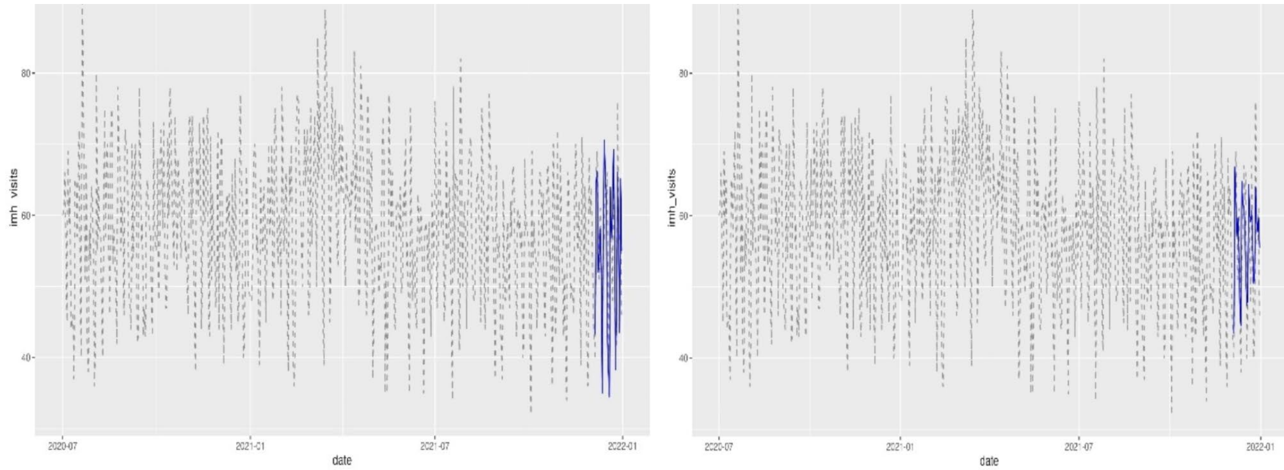

Fig. 2. Illustrative results using a new Twitter indicator (*Tweet Count*) as an enhanced ARIMA forecasting model to forecast *IMH Visits*. (left) Prediction of *IMH Visits* using baseline model of lagged values of *IMH Visits* itself with two lag days (blue = predicted values, grey = actual values), (right) Prediction of *IMH Visits* using both lagged values of *IMH Visits* and *Tweet Count* with two lag days (blue = predicted values, grey = actual values).

Model no.	ARIMA model [lag day]	Model prediction error	
		RMSE	MAE
1	Mindline Crisis [1]	4·75	4·06
2	Mindline Crisis + Sadness Count [1]	5·98	5·28
3	Mindline Crisis + Joy Intensity [1]	5·86	5·38
4	Mindline Crisis + Anger Count [1]	4·75	4·05
5	Mindline Crisis [3]	5·99	5·25
6	Mindline Crisis + Tweet Count [3]	5·11	4·54
7	Mindline Crisis [5]	5·29	4·53
8	**Mindline Crisis + Joy Count [5]**	**4·48**	**3·81**

Table 3. Error scores for each ARIMA model with and without additional χ variable in modelling Mindline Crisis. Results are sorted based on lowest to highest RMSE scores; lower RMSE indicates better models.

forecasting scenario using a 95:5 split of training and test data. The results showed that among all the ARIMA models tested, *IMH Visits* + *Tweet Count* with two lag days has the smallest forecasting error, resulting in an RMSE error value of 6·83 (Table 2). Adding *Tweet Count* and *New Cases* indicators as the *X* variable leads to an improvement (i.e., smaller RMSE errors) in modelling the *Y* variable, *IMH Visits*.

In mapping the performance difference between the predicted vs. actual scenarios, we highlight an example (Fig. 2) where model no. 1 (RMSE = 6·83) predicted the actual IMH visits better than model no. 6 (RMSE = 7·64).

Mindline crisis

In modelling the *Y* variable *Mindline Crisis*, the best-performing model based on the RMSE score is one that incorporates both the lagged values of *Mindline Crisis* and *Joy Count* with five lag days (RMSE = 4·48; Table 3). This model performs better than the baseline model using lagged values of *Mindline Crisis* of 5 lag days alone (RMSE = 5·29; Table 3). Incorporating *Tweet Count* to *Mindline Crisis* of three lag days also helped to improve the model (RMSE = 5·11 vs. 5·99; Table 3).

In mapping the performance difference between the predicted vs. actual scenarios, we highlight an example (Fig. 3) where model no. 8 (RMSE = 4.48) predicted the actual IMH Visits better than model no. 7 (RMSE = 5.29). Here, there is no marked visual difference in the predicted results, largely due to the very small overall fluctuation in the predicted period.

Discussion

We used multi-source big data surrounding mental health-related factors and advanced emotion analysis algorithms to drive a wide range of novel early indicators, i.e., the count, the percentage, and the intensity of fear,

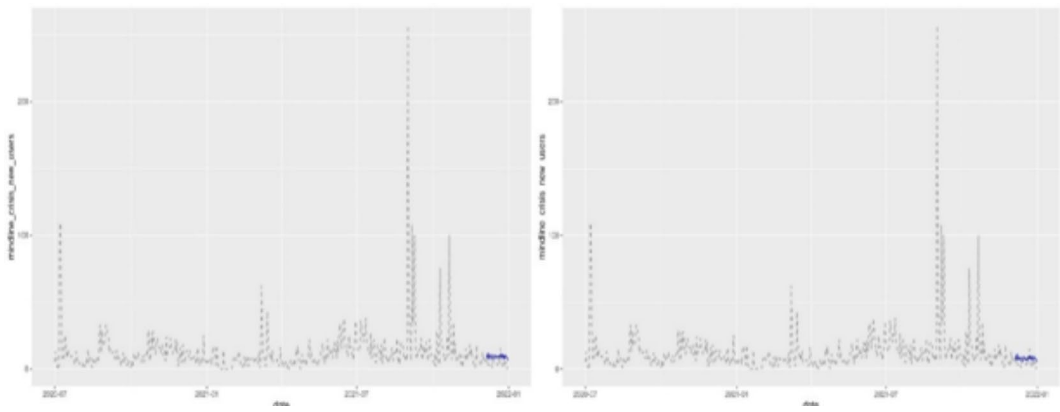

Fig. 3. Illustrative results using a new Twitter indicator (*Tweet Joy Count*) as an enhanced ARIMA forecasting model to forecast *Mindline Crisis*. (left) Prediction of *Mindline Crisis* using lagged values of *Mindline Crisis* itself with five lag days, (right) Prediction of *Mindline Crisis* using both lagged values of *Mindline Crisis* and *Tweet Joy Count* with five lag days.

anger, sadness, and joy emotions expressed on Twitter, for predicting national-level mental healthcare needs and demand in the heightened period of the COVID-19 pandemic.

Emotion indicators extracted from Twitter, especially the joy and anger emotions, can enhance the prediction of downstream mental health needs measured in both IMH and Mindline sources. Joy Intensity, the daily average intensity value of joy-related expressions on Twitter posts extracted using the CrystalFeel algorithms, significantly improved the prediction of IMH emergency room visits and crisis cases in Mindline as early as one lag day. The daily number of tweets that expressed anger, *Anger Count*, was also significantly helpful in predicting both *IMH Visits* and *Mindline Crisis* (at four lag days and one lag day, respectively). In contrast, broad situation indicators commonly used in the COVID-19 period, except for *New Cases* and *Announcement Count*, were not helpful in predicting mental health needs. None of the five situation indicators helped predict the *Mindline Crisis*.

Evaluating the performance of the ARIMA models based on the Granger-causality results further highlights the potential practical value of emotion indicators as early predictors in predicting mental health needs. In predicting both emergency room visits and Mindline users in the "Crisis" mental status, the best-performing model by RMSE score is the one with social media variables incorporated: *Tweet Count* with two lag days in the case of predicting *IMH Visits* and *Joy Count* with five lag days in the case of predicting *Mindline Crisis*. Even when RMSE error values are reduced and higher prediction accuracies are obtained by incorporating social media variables into the model, incorporating additional situational or social media variables does not always help improve the models. For instance, in *IMH Visits* and *Mindline Crisis* at one lag day, the use of its own lagged values results in a lower RMSE score compared with the incorporation of other variables. This "fluctuation" is expected as the relative usefulness of the enhancement models may vary based on the selection of the period for the model used in forecasting.

Different emotions and emotion-derived indicators differed in their predictive value. While our results showed that indicators associated with joy and anger, such as *Joy Intensity*, *Joy Count* and *Anger Count*, were useful in predicting mental health needs, the fear-related and sadness-related indicators generally did not indicate similar usefulness for any mental healthcare needs data (with the only exception being *Sadness Count* on *Mindline Crisis*). This is likely associated with fear and sadness carrying lower action tendencies than the joy and anger emotions[18,19]. Interestingly, as the only exception, *Sadness Count* was found to have a significant Granger-causality effect in predicting *Mindline Crisis*. This implies that the number of sad tweets on Twitter could be a better prediction variable of the Mindline users in the "Crisis" mental status, likely due to the similarity in people using online channels. As people who are experiencing a "Crisis" mental state may not choose to seek help in psychiatric hospitals, future studies should focus on the unique value of measuring the number of sad expressions from social media platforms.

There are limitations to this study that should be addressed in future studies. First, our analysis focuses on exploring the predictive value of social media indicators using statistical forecasting tests, i.e., Granger-causality tests. The Granger-causality tests do not examine the directional correlation between a specific emotion and a specific change in mental health needs. Instead, the Granger-causality test verifies whether the information within a time-series variable (e.g., the count of joy expressed on Twitter) significantly helps to predict another time-series variable (e.g., the count of visits to the IMH emergency room). However, despite the naming convention, Granger-causality tests do not test for true causality and do not examine the direction (positively or negatively) with which the variables are associated, given that many lags and lag-specific relationships are involved in time-series data. During the protracted COVID-19 period and under differing situations, people may hold off their plan to go to the emergency room until the virus is contained or the lockdown is lifted. Some may wait until the point where "the last straw that breaks the camel's back" is achieved. The exact mechanism explaining how emotions expressed on social media are associated with mental health care-seeking behaviours, particularly during changing situations, will require future research.

Second, we employed Granger causality tests to elucidate the possible pairwise effects of *each* situational and social media indicator in predicting mental healthcare needs. Our study does not include potential variables such as age, gender or socio-economic status and the presence of stressors such as drug abuse or domestic violence, illnesses, relationship problems or financial problems[20–22]. Such variables were not included in our analysis as auxiliary variables as they were unavailable on a daily basis for our study's time-series forecasting model analysis. Hence, selection bias of the data variables used in our study may be present due to the nature of our data sources and the absence of additional information that assesses the data usability for a public mental health forecasting model. Future studies should consider novel ways of capturing such data and variables in the model when predicting public mental health needs.

Third, this study used data collected from Twitter and employed the CrystalFeel algorithms to extract emotion information. They were hosted as APIs for research use and can potentially present sustainable data and tools for a predictive system. Despite the innovativeness of our approach, it is useful to note that selection bias may be inherent to the users of the chosen social media platform and emotion analysis algorithms. Future studies that develop mental health early sensing systems will benefit from including additional social media data sources and algorithms as they are available, especially at little to no cost and access barriers. Furthermore, as the COVID-19 pandemic has neither entirely ended nor become endemic, new data and the development of new tools will enable future studies to examine the even longer-term impact of the COVID-19 pandemic on mental health.

Given the promise shown by the study results, it is reasonable to postulate that future research combining multiple social indicators and experimenting with different predictive models may allow us to further understand the feasibility of a real-world deployable mental health needs predictive system. Future studies should consider employing models that can take into account multiple variables that may influence emotions on social media platforms and mental health care-seeking behaviours. Such systems will subsequently allow government officials and healthcare authorities to make informed decisions on allocating resources, such as pre-emptive staffing planning during emergencies, to meet the public needs for mental healthcare resources. Future research examining the value of the study's data and methods for other applications and longer-term planning support, such as judging the effectiveness of education campaigns and countering misinformation, can also lead to improved and proactive responses addressing public health needs.

To conclude, our research demonstrated that despite the low signal-to-noise ratio from social media data, fine-grained social media indicators extracted using nascent emotion analysis algorithms show promise in the early prediction of possible heightened needs in general mental healthcare needs, especially with the significant relationship found with downstream data such as emergency room visits. Real-time monitoring and assessment of comments by social media users can provide new indicators for tracking and forecasting population-level mental health states and needs. Policymakers and mental healthcare service providers may be able to use these new predictive capabilities to project demand for mental health services and adjust resourcing to cope with anticipated increases or changes in needs. Timely and pre-emptive responses include allocating additional employees to address high phone call volumes in mental health hotlines during specific periods and improving access to mental health experts.

Methods

The study was approved as "Exemption from full A*STAR IRB Review" (institutional review board reference number 2020 – 258) for using social media data obtained from approved Twitter APIs and existing anonymous public data approved by data providers to study research topics surrounding the COVID-19 outbreak.

To examine the research questions, we collected daily-level time-series data from multiple public sources concerning Singapore's heightening and stabilising phases, covering 18 months from July 2020 to December 2021.

Data and indicators selection criteria

As the study's purpose is to examine new data and tools that can be used as predictors to forecast downstream mental healthcare needs, the first and primary criterion is that the data and indicator extraction methods need to be accessible without any substantially high cost or barrier to collect.

Second, the data should be available continuously for time-series statistical analysis. This means that traditional survey data, collected every several months, are not usable for forecasting daily mental healthcare needs.

Third, the data and tools should have demonstrable validity, such as those shown by prior studies or their use in adjacent problem domains.

Situation data and indicators

For situation indicators, we used data sources published by the health authorities as they are routinely collected and reported to the public as primary indicators of the severity of the COVID-19 situation. The indicators include COVID-19 cases and COVID-19 deaths in daily new cases and accumulated case counts from WHO[23]. In addition, we collected the daily number of government announcements from MOH[24] to serve as a proxy for the intensity of government actions to manage the COVID-19 situation. These indicators are used as comparative predictors for our study.

Social media data, data pre-processing and emotion indicators

For social media sources, we used Twitter as it provides public access to the post's text content, user screen name, timestamp, and other relevant information for academic use via an application programming interface (API)[25]. We performed a keyword search and obtained tweets that contained at least one of the COVID-19-related keywords: "ncov", "corona" and "covid". For this study, we used the Singapore-based tweets dataset, which was selected based on the location disclosed by the tweet authors' public profile. The details of the Twitter dataset can be found in Gupta et al.[26].

To extract effective early indicators from the highly noisy social media data sources, we applied the following data processing and variable extraction steps: (i) clean the data, (ii) perform emotion classification and intensity measurement, (iii) prepare the final study data in daily aggregated forms for statistical analyses, and (iv) pre-process the aggregated data. We first cleaned the social media data by applying troll removal, that is, removing duplicated posts, posts considered as click baits or financial investment ads (e.g. comments with "bitcoin", "click here", "inbox me"), email addresses, and 1-character-only posts. We also removed tweets posted by influencers (news agencies, political leaders, etc.) by using the "followers: following" ratio[27], where a ratio of more than 1 would be deemed as an influencer. By removing such tweets, we aim to obtain data that more accurately reflects general public emotions. The final Twitter data used for this study, consisting of 140,598 tweets, were obtained after removing 2,335 potential trolls and 234,830 tweets from possible influencers.

For emotion indicators, we used CrystalFeel[28] as the API that allows the systematic processing of large-scale data for academic use. CrystalFeel is a multidimensional emotion analysis software package using Support Vector Machine (SVM)-trained algorithms. It can classify the emotion (joy, anger, fear, and sadness) and measure the intensity of the emotion in a given text, such as a tweet or Facebook comment[28,29].

Most sentiment analysis algorithms consider sentiments and emotions in a *categorical* sense, which typically attempts to assign a tweet into positive, negative, or neutral classes or a happy vs. not happy, sad vs. no sad category. CrystalFeel's key feature is the ability to quantify a tweet's *intensity* level over four primary emotions – fear, anger, sadness, and joy – on a continuous scale of 0–1 (e.g., 0 indicates the absence of fear being expressed; 1 indicates an extremely high intensity of fear being expressed in the tweet). It also automatically classifies each tweet into one of the Fear, Anger, Sadness, Joy, or No Specific Emotion categories.

The CrystalFeel algorithms' emotion intensity measurement accuracy has been validated in a SemEval-18 task[30], where it achieved high Pearson correlation coefficients when evaluated against human-labelled emotion intensity scores: 0.816 (overall emotion or sentiment valence intensity), 0.708 (joy intensity), 0.740 (anger intensity), 0.700 (fear intensity) and 0.720 (sadness intensity)[29]. Some of CrystalFeel's features have been found useful in other COVID-19 social media sentiment analysis studies[31–34]. Its predictive validity has been examined and tested to be useful in other natural language processing (NLP) tasks, including predicting the agency and social ingredients of happy moments[35], predicting popular news on Facebook and Twitter[36], detecting propaganda techniques in tweets[37], predicting video-level multimodal emotions from YouTube videos[38] and predicting user-level past vs. future temporal orientation[39].

In this study, we used CrystalFeel's full range of emotion analysis features, which cover the classification of the emotion class and the intensity value associated with the emotions of fear, anger, joy, and sadness, with examples of the emotion analysis results of tweets indicated (Table 4).

Mental healthcare needs measures – IMH visits and Mindline Crisis

For mental health needs indicators, we used behavioural data that indicate how the public develops online and offline mental health needs over time. Data were taken from official governmental mental health needs services, from (1) psychiatric hospital emergency room visits and (2) online self-help portal.

The need for mental healthcare needs is reflected in the daily count of visitors to the emergency room from the Institute of Mental Health (IMH)[40], the country's primary psychiatric care hospital, which we used as the main proxy of the public need to approach psychiatric services for their mental health concerns.

Data from Mindline[41] was used to indicate mental health needs expressed online. Mindline is an online mental health help portal created by the Ministry of Health Office for Healthcare Transformation (MOHT), a government-created entity. Mindline was set up in June 2020 amid COVID-19, when the population's mental health could be adversely affected due to uncertainties, unemployment, and isolation. A primary feature of Mindline is to present the users with a mental health status questionnaire consisting of 16 items from standardised mental health screening instruments that are clinically validated to be suitable for self-administration, namely the 9-item Patient Health Questionnaire (PHQ-9)[42] and the 7-item General Anxiety Disorder test (GAD-7)[43].

In addition, respondents were asked to indicate the frequency at which they experienced each item (e.g., "Not being able to stop or control worrying") on a 0–3 scale (0-Not at all, 3-Nearly every day) in response to the question "Over the last 2 weeks, how often have you been bothered by the following problems?".

Example	Emotion Class	Intensity			
		Fear	Anger	Joy	Sadness
"We are good in many implementations in last few years Can we excel in health infra for covid as well"	No specific emotion	0.291	0.394	0.370	0.305
"Im scared going back to the office next week The travelling the touching of public places and the restriction"	Fear	0.746	0.518	0.240	0.589
"Commonsense is clearly not common facemaskshelp dontbestupid"	Anger	0.403	0.424	0.194	0.421
"depression seeing the cases rise here along with the number of deaths related to covid Im just feeling myself spiral deeper into depression and feeling like whatever Im doing right now is hopeless"	Sadness	0.821	0.572	0.122	0.850
"On Doctor's Day I salute our brave Doctors who have been leading the battle against COVID19 at the forefront"	Joy	0.350	0.368	0.430	0.358

Table 4. Examples of social media data emotion classification and emotion intensity measurement (n_Twitter = 140,598).

mindline.sg Protocol Terms	Well	Mild	Moderate		Crisis
Severity on PHQ-9	None/ Minimal Score (0–4)	Mild Score (5–9)	Moderate Score (10–14)	Moderately Severe Score (15–19)	Severe Score (20–27)
Severity on GAD-7	Minimal GAD-7 $\leq$ 4	Mild 5 $\leq$ GAD-7 $\leq$ 9	Moderate GAD-7 $\geq$ 10	Severe GAD-7 $\geq$ 10	NA

Table 5. The protocol terms of Mindline severity levels and the correspondence with PHQ-9 and GAD-7.

Variable category (Number of variables in this category)	Variable name	Measurement/meaning	Value range in the data
Mental health needs measures (2)	IMH Visits	Daily accumulated number of users who visited IMH Emergency Room	32–89
	Mindline Crisis	Daily number of new users who used mindline.sg website, which is assessed as in the "crisis" status	0–257
Twitter Indicators (13)	Tweet Count	Daily number of COVID-19-related tweets from Twitter users publicly declared to be from Singapore	62–860
	Fear Count	Daily number of COVID-19-related tweets from Twitter users publicly declared to be from Singapore, that express fear	18–427
	Anger Count	Daily number of COVID-19-related tweets from Twitter users publicly declared to be from Singapore, that express anger	10–292
	Sadness Count	Daily count of the number of COVID-19-related tweets with Twitter users publicly declared to be from Singapore, that express sadness	1–115
	Joy Count	Daily count of the number of COVID-19-related tweets from Twitter users publicly declared to be from Singapore, that express joy	15–240
	Fear Percentage	Daily frequency of COVID-19-related tweets from Twitter users publicly declared to be from Singapore, that express fear, in relation to the daily tweet count (Tweet Count)	10.1–72.7%
	Anger Percentage	Daily frequency of COVID-19-related tweets from Twitter users publicly declared to be from Singapore, that express anger, in relation to the daily tweet count (Tweet Count)	6.3–49.5%
	Sadness Percentage	Daily frequency of COVID-19-related tweets from Twitter users publicly declared to be from Singapore, that express sadness, in relation to the daily tweet count (Tweet Count)	0.7–17.0%
	Joy Percentage	Daily frequency of COVID-19-related tweets from Twitter users publicly declared to be from Singapore, that express joy, in relation to the daily tweet count (Tweet Count)	9.9–62.8%
	Fear Intensity	Daily average fear intensity score of COVID-19-related tweets that express fear	0.492–0.587
	Anger Intensity	Daily average anger intensity score of COVID-19-related tweets that express anger	0.460–0.594
	Sadness Intensity	Daily average sadness intensity score of COVID-19-related tweets that express sadness	0.415–0.662
	Joy Intensity	Daily average joy intensity score of COVID-19-related tweets that express joy	0.356–0.452
Situation Indicators (5)	New Cases Count	Daily number of new COVID-19 cases reported by MOH to WHO	0–5,324
	Cumulative Cases Count	Daily accumulated number of cases reported by MOH to WHO	1–279,061
	New Deaths Count	Daily number of new deaths reported by MOH to WHO	0–18
	Cumulative Deaths Count	Daily accumulated number of deaths reported by MOH to WHO	0–827
	Announcement Count	Daily number of announcements by MOH	0–18

Table 6. Data dictionary - summary of all variables used in this study. The variables or indicators are listed within each category from the most coarse-grained to the most fine-grained.

The scores of the responses were then summed up and categorised into four mental distress severity levels: 'Well', 'Mild', 'Moderate', or 'Crisis' based on a protocol term (Table 5). Different resources were recommended to the user according to the levels. For example, people with "Well" status were recommended to websites that can help them maintain their well-being, and people with "Crisis" status were asked to seek immediate help from a list of 24-hour hotlines. More details on Mindline's development can be found in Weng et al.[44].

For this study, we focus on analysing the user visit trends with self-assessment results in a "Crisis" situation, which reflects the most severe mental health status. Further, to focus on organic visits to Mindline, we removed the user visits led by marketing campaigns from the data.

Summary of all variables used in this study
A definition of all the study variables and the manner in which they were obtained is given below (Table 6).

Statistical analysis – pre-processing aggregated data

Before carrying out the statistical analysis, we pre-processed all the daily aggregated data by normalising the data with a Z-score, using "first difference" to ensure stationarity, removing volatility by dividing by monthly standard deviation, and removing seasonality by subtracting monthly means as a prerequisite to analysing the time-series data. The Augmented Dickey-Fuller Test was used to verify that the variables were stationary.

Granger causality tests

The Granger causality test was used to investigate the dynamic relations between situational and Twitter indicators, as well as mental healthcare needs data. We used Python 3.6.10, including the following packages: Pandas 1.0.1, Numpy 1.19.5, Statsmodels 0.10.0rc2, and NLTK 3.4.5 on Anaconda 3-2019.10, for our analysis.

Granger causality estimates the causal effects of one time-series variable on another time-series variable after controlling for lagged values. It determines whether lagged values of and predicts better than lagged values of alone[45,46]. For instance, in investigating the relationship between the "Fear Count" (x_t), and "IMH visits" (y_t), is modelled as:

$$y_t = \alpha_0 + \sum_{l=1}^{L} \alpha_l y_{t-l} + \sum_{l=1}^{L} \beta_l x_{t-l} + \epsilon_t$$

where L refers to the total number of lagged values, α_1 are the regression weights on y_{t-l}, β_l is the regression weights on x_{t-l} and ϵ_t is the time-variant residuals.

We used likelihood-ratio tests to determine the optimal lag length for each pair of variables. The series (x_t) is considered Granger-cause series (y_t) if the P-value is 0.05 or less. This study reports the earliest significant lag days. After a review of the P-value results, we found that increasing the number of lag days beyond five days did not improve the results. Other Granger causality studies have also tested lag days of up to 5 days[47] or up to 7 days[48,49]. As such, we chose five days as the maximum lag days for the Granger causality tests.

However, it is useful to note that despite its name, the Granger-causality test does not test for true causality. One limitation of employing Granger Causality is that it is a bivariate analysis and does not factor in other predictors' effects simultaneously. Further research should use a multivariate model to examine the combined effects of multiple predictors on the outcome variable.

ARIMA forecasting

We evaluated the performance of auto-regressive integrated moving average (ARIMA) models in forecasting based on the significant variables revealed from the Granger-causality results. We compared each ARIMA model with and without the additional lagged values of χ variable in predicting *y* variable. We performed a 95:5 split, where the first 95% of the data (n=522) was used for training, whilst the remaining 5% (n=27) was used for testing.

In an ARIMA model, the *y* variable is forecast using lagged values of the variable itself, as seen in Eq. (1) below. In our analysis, we evaluated the performance of this baseline model with other models incorporating additional *x* variables. The model would then comprise lagged values of the *y* variable and lagged values with the additional *x* variable, as seen in Eq. (2) below[50].

(1) Without additional *x* variable: $y_t = \alpha_0 + \sum_{l=1}^{L} \alpha_l y_{t-l} + \epsilon_t$
(2) With additional *x* variable: $y_t = \alpha_0 + \sum_{l=1}^{L} \alpha_l y_{t-l} + \sum_{l=1}^{L} \beta_l x_{t-l} + \epsilon_t$

In the analysis, we used two error metrics: Root Mean Square Error (RMSE) and Mean Absolute Error (MAE)[51]. RMSE is a commonly used scale-dependent error measure that shows prediction error from the observed values using Euclidean distance[52] (C3.ai, 2024). MAE is a commonly used forecast error measure which refers to the summation of absolute errors between each forecast value and real value, divided by the number of errors.

A lower error value for both metrics indicates that the model is performing better. We focus on RMSE as it helps show the observed value and illustrate the potential practical value of the new ARIMA forecasting model. The ARIMA models and the error rates were computed in R programming language using the fpp3 package[53].

Data availability

The daily aggregated time-series data used in this study (including actual values and normalised values) are available in the figshare repository, DOI: https://doi.org/10.6084/m9.figshare.26963491. The count of daily emergency room visits data ("IMH Visits") is available from the corresponding author upon reasonable request.

Code Availability

The source scripts for social media data pre-processing are available on this GitHub page: https://github.com/atiqaho/mental_wellbeing_covid_sg. CrystalFeel API is accessible via https://socialanalyticsplus.net/crystalfeel.

Received: 13 April 2023; Accepted: 23 September 2024
Published online: 05 October 2024

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Acknowledgements
This study was supported by the Agency for Science, Technology and Research (A*STAR), Singapore, under A*CRUSE (COVID-19 social media analytics project). We thank MOHT's Julian Chang Kui Yu for his assistance and helpful discussion on the mindline.sg data. The manuscript also benefited from the helpful comments from Ng Hoek Hee from the A*STAR Research Office.

Author contributions
NAO and CP performed the literature search, synthesised the study data and performed the data analysis, drafted the manuscript, and contributed equally to the study. MZ and SL performed data processing and cleaning and verified the underlying data reported in the study. SL performed an additional statistical analysis that compared error rates between the base and enhanced models. RG provided the social media data with processed emotion results and analysis. WM, YSP, RJTM, and WCL contributed to the conceptualisation of the study and provided the mindline.sg data and contributed to the discussion of the results. KBT provided inputs to the data analysis method and results discussion. MS contributed to the study design, provided the IMH emergency room visits data, and contributed to interpreting the results. YY initiated the study, conceptualised the analytical framework, and led the overall manuscript. All authors read and approved the final manuscript.

Declarations

Competing interests
RG and YY are co-inventors of the CrystalFeel algorithm. The other authors declare no competing interests.

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