

Social Media Reveals Psychosocial Effects of the COVID-19 Pandemic

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Abstract

Background: The novel coronavirus disease 2019 (COVID-19) pandemic has caused several disruptions in personal and collective lives worldwide. The uncertainties surrounding the pandemic have also led to multi-faceted mental health concerns, which can be exacerbated with precautionary measures such as social distancing and self-quarantining, as well as societal impacts such as economic downturn and job loss. Despite noting this as a “mental health tsunami,” the psychological effects of the COVID-19 crisis remains unexplored at scale. Consequently, public health stakeholders are currently limited in identifying ways to provide timely and tailored support during these circumstances.

Objective: Our work aims to provide insights regarding people’s psychosocial concerns during the COVID-19 pandemic by leveraging social media data. We aim to study the temporal and linguistic changes in symptomatic mental health and support-seeking expressions in the pandemic context.

Methods: We obtain ~60M Twitter streaming posts originating from the U.S. from 24 March-24 May 2020, and compare these with ~40M posts from a comparable period in 2019 to causally attribute the effect of COVID-19 on people’s social media self-disclosure. Using these datasets, we study people’s self-disclosure on social media in terms of symptomatic mental health concerns and expressions seeking support. We employ transfer learning classifiers that identify the social media language indicative of mental health outcomes (anxiety, depression, stress, and suicidal ideation) and support (emotional and informational support). We then examine the changes in psychosocial expressions over time and language, comparing the 2020 and 2019 datasets.

Results: We find that all of the examined psychosocial expressions have significantly increased during the COVID-19 crisis – mental health symptomatic expressions have increased by ~14%, and support seeking expressions have increased by ~5%, both thematically related to COVID-19. We also observe a steady decline and eventual plateauing in these expressions during the COVID-19 pandemic, which may have been due to habituation or due to supportive policy measures enacted during this period. Our language analyses highlight that people express concerns that are contextually related to the COVID-19 crisis.

Conclusions: We studied the psychosocial effects of the COVID-19 crisis by using social media data from 2020, finding that people’s mental health symptomatic and support-seeking expressions significantly increased during the COVID-19 period as compared to similar data from 2019. However, this effect gradually lessened over time, suggesting that people adapted to the circumstances and their “new normal”. Our linguistic analyses revealed that people expressed mental health concerns regarding personal and professional challenges, healthcare and precautionary measures, and pandemic-related awareness. This work shows the potential to provide insights to mental healthcare and stakeholders and policymakers in planning and implementing measures to mitigate mental health risks amidst the health crisis.

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Original Manuscript

Original Paper

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Background: The novel coronavirus disease 2019 (COVID-19) pandemic has caused several disruptions in personal and collective lives worldwide. The uncertainties surrounding the pandemic have also led to multi-faceted mental health concerns, which can be exacerbated with precautionary measures such as social distancing and self-quarantining, as well as societal impacts such as economic downturn and job loss. Despite noting this as a “mental health tsunami,” the psychological effects of the COVID-19 crisis remains unexplored at scale. Consequently, public health stakeholders are currently limited in identifying ways to provide timely and tailored support during these circumstances.

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Keywords: social media; Twitter; language; psychosocial effects; mental health; transfer learning; depression; anxiety; stress; social support; emotions; COVID-19; coronavirus; crisis

Introduction

The impacts of global public health emergencies extend beyond medical repercussions – they affect individuals and societies on many levels, causing disruptions [1, 2]. In an article written by the American Psychological Association following the Ebola outbreak [3], the epidemic was described as an “epidemic of fear” – in the United States, it was described by the media as “fearbola,” to describe a paranoia that infected the country. Reports of similar feelings of anxiety, stress, and uncertainty have been repeatedly reported during other global outbreaks and pandemics [4]. The ongoing outbreak of the coronavirus, SARS-COV-2, has led to a pandemic of illness (coronavirus disease, or COVID-19) that has globally caused 16M cases and 700K deaths, reported as of the end of July 2020 [5]. According to recent surveys from the Census Bureau and the Centers for Disease Control and Prevention and other studies, the COVID-19 crisis has been reported to be associated with rapid rises in psychological distress across many nations [6], with women, the young, the less educated, and some ethnic minority groups reporting greater mental health strain [7]. On the one hand, persons are worried about the direct effects of potential infection, including fears of death, lasting disabilities, or exacerbating chronic illnesses. On the other, actions to mitigate the spread of COVID-19, including social distancing, quarantines, and business closures with resulting job losses, are a powerful source of life disruptions and emotional distress.

Fear and anxiety about a disease as infectious as COVID-19 can trigger new-onset or exacerbate existing mental illness [8]. Therefore, the practical impact of the crisis is far greater than the actual number of infection cases or fatalities [9]. While expressions of distress may stem from concern and worry relating to the direct impacts of the disease, they may relate as much to disruption of regular routines, sleep and eating patterns, having out-of-school children at home full-time, economic hardships and unusual volatility in financial markets, and forced geographical displacement or confinement. Indeed, some people are at risk of developing post-traumatic distress due to exposure to the multi-faceted uncertainties, or from confronting dying persons or lost loved ones. While disease mitigating efforts such as “social distancing” and “self-quarantining” are recommended [10–13], individuals in medical isolation may experience increased symptoms of anxiety and depression, as well as feelings of fear, abandonment, loneliness, and stigmatization [14, 15].

Despite concerns about the myriad of social and behavioral issues associated with the COVID-19 pandemic [16, 17], research has been scant to examine its psychosocial impacts or how to predict and mitigate them. Although it is anticipated that COVID-19 will have broadly ramifying effects [18, 19], public health workers and crisis interventionists are limited in their ability to extend services and support in a timely, preemptive fashion. Although surveys are a step forward to support such efforts [7], due to their retrospective recall bias, limited scalability, and without being able to provide real-time insights, public health workers are not only unable to prioritize services for the most vulnerable populations, but more specifically, less equipped to direct prevention efforts towards individuals with greater propensities for adverse psychological impacts.

This paper seeks to address the above gap by drawing insights into people’s expressed mental health concerns by leveraging social media data. The rise in online and social media activity has provided an unprecedented opportunity to enhance the identification and monitoring strategies of various mental and psychosocial disorders [20, 21]. Over 80% of U.S. adults use social media daily [22],

placing it ahead of texting, email, and instant messaging, and disclose considerably more about themselves online than offline [23, 24]. Social media provides a real-time platform where people often candidly self-disclose their concerns, opinions, and struggles during this pandemic [25]. Our research is, therefore, founded on prior work to understand people's psychosocial distress in terms of their symptomatic mental health expressions of anxiety, depression, stress, and suicidal ideation, and their expressions seeking emotional and informational support [20, 26–28].

Methods

Data

To study people's psychosocial expressions on social media, we obtain Twitter data. Twitter is one of the most popular social media platforms [29], and its public-facing, micro-blogging based design enables people to candidly self-disclose and self-express their life experiences and concerns [30].

Treatment Data. In particular, we focus our study on the U.S. population and leverage the Twitter streaming API. Using geo-bounded coordinates, we collect 1% of real-time Twitter data originating from the U.S. We collect 59,096,694 Twitter posts between March 24, 2020, and May 24, 2020. Because this dataset comes from the same period when the COVID-19 outbreak occurred, we label this dataset as the *Treatment* dataset. We note that this period saw an exponential growth in reported COVID-19 infection cases (~50K to ~1M) and fatalities (~1K to ~56K) in the U.S. [31]. During these two months, federal and state policies and laws were enacted to control or mitigate the spread of the outbreak, including school and work closures, stay-at-home orders, and Coronavirus Aid, Relief, and Economic Security Act [32].

Control Data. To understand the social media expressions particularly attributed to the COVID-19 crisis, we obtain a control dataset that originates from the same geographical location (U.S.) and similar time period, but from the previous year (2019). Prior work [33] motivates this approach of obtaining control data that acts as a baseline and likely minimizes confounding effects due to geo-temporal seasonality in lifestyle, activities, experiences, and unrelated events that may have some psychosocial bearing. We obtain a similarly-sized dataset of 40,875,185 Twitter posts shared between March 24, 2019, and May 24, 2019.

Psychosocial Effects of COVID-19

To understand the psychosocial impacts of the COVID-19 outbreak, we conduct two types of analysis on our Twitter dataset, which we describe below. Our work builds upon the vast, rapidly growing literature studying mental health concerns and psychosocial expressions within social media data [20, 23, 26–28, 30, 34–37].

Symptomatic Mental Health Expressions

Drawing on the work referenced above, we hypothesize that people's self-disclosure expressions on social media can reveal symptomatic mental health expressions attributed to the COVID-19 crisis. We examine symptomatic expressions of anxiety, depression, stress, and suicidal ideation. These are not only some of the most critical mental health concerns but also have been attributed to be consequences of the pandemic outbreak [16, 38, 39].

To identify mental health symptomatic expressions in social media language, Saha et al. (2019) built machine learning classifiers [28] using transfer learning methodologies --- the main idea here is to infer mental health attributes in an unlabeled data by transferring a classifier trained on a different labeled dataset. These classifiers are n -gram ($n=1,2,3$) based binary Support Vector Machine (SVM) models where the positive class of the training datasets stems from appropriate Reddit communities

(*r/depression* for depression, *r/anxiety* for anxiety, *r/stress* for stress, and *r/SuicideWatch* for suicidal ideation), and the negative class of training datasets comes from non-mental health-related content on Reddit — a collated sample of 20M posts, gathered from 20 subreddits from the landing page of Reddit during appropriately the same period as the mental health subreddit posts, such as *r/AskReddit*, *r/aww*, *r/movies*, and others. These classifiers perform at a high accuracy of approximately 0.90 on average on held-out test data [28].

Clinical Validity. Saha et al.'s classifiers, used here, have also been shown to transfer well on Twitter with an 87% agreement between machine-predicted labels and expert appraisal [28], where experts annotated posts in the classification test data using DSM-5 [40] criteria of mental health symptoms. Bagroy et al. [41] reported additional validation of such derived insights with feedback from clinical experts. In this work, the outcomes of the mental health expression classifiers were compared with those given by human coders on the same (random) sample of social media posts; the latter coded the posts based on a codebook developed using prior qualitative and quantitative studies of mental health disclosures on social media and literature in psychology on markers of mental health expressions. Coders not only agreed with the outcomes of the classifiers (Cohen's κ was 0.83), but also noted that the classifiers could identify explicit expressions of first-hand experience of psychological distress or mental health concerns ("i get overwhelmingly depressed") as well as expressions of support, help, or advice seeking around difficult life challenges and experiences ("are there any resources I can use to talk to someone about depression?"). Further details about these classifiers, including their detailed performance, predictive features demonstrating model interpretability, and efficacy of transfer to Twitter data, may be found in [28,33,41]. We use these classifiers to machine label both our *Treatment* and *Control* datasets.

Support-seeking Expressions

Social support is considered an essential component in helping people cope with psychological distress [42]. Research reports that supportive interactions can even have a "buffering effect" [43]; that is, they can be protective against the negative consequences of mental health. With the wide adoption of web and social media technologies, support-seeking is increasingly happening online and has been shown to be efficacious [23, 44]. In fact, a meta-analysis indicates that online support is effective in decreasing depression and increasing self-efficacy and quality of life [45]. In the context of suicide, certain types of social support in Reddit communities may reduce the chances of future suicidal ideation among those seeking mental health help [46]. Oh et al. further showed that surveyed Facebook users demonstrate a positive relationship between having health concerns and seeking health-related social support [47]. Indeed, during global crises such as COVID-19, when many of the physical sites for healthcare (including mental health) have been closed or have very restricted access, it is likely that online support has proliferated [48]. Fear of potential infection may further have alienated individuals in need to pursue formal treatment, therapy, and support, perhaps channelizing their support seeking efforts online and on social media.

According to the "Social Support Behavioral Code" [49], two forms of support that have received theoretical and empirical attention are emotional and informational support. Emotional support (ES) corresponds to empathy, encouragement, and kindness, while informational support (IS) corresponds to information, guidance, and suggestions [50, 51]. These two forms of support have been found to be most prevalent and effective in several studies of online support and social media [46, 50, 52, 53]. Social media enable individuals to self-disclose and express in making their emotional and informational needs known and sought [53]. Andalibi et al. found that these two kinds of support can co-occur with other forms of support, such as posts seeking emotional support often seek esteem and network support [52], and Attai et al. noted that Twitter is effective in seeking and providing health-related informational needs [54], contextually related with our problem of interest.

To identify support expressions on social media, we use an expert-appraised dataset and classifier built in prior work [50,55]. These are binary SVM classifiers identifying the degree (high/low) of ES and IS in social media posts. When the predictions of these classifiers were cross-validated with expert annotations from Sharma and De Choudhury's data [50], the classifiers were found to have k -fold cross-validation accuracies of 0.71 and 0.77 in ES and IS classifications respectively [55]. Similar to the symptomatic expressions classifiers, the classifiers of support expressions are transferred from Reddit and typically performs well in our dataset due to the high linguistic equivalence between Reddit and Twitter datasets [35]. We further manually inspect a random set of 125 Twitter posts in our dataset using the methods outlined in prior work [28, 41] to rate each Twitter post with binary high or low ES and IS. We find that the manual ratings and classifier ratings show a high agreement of 88% and 93%, respectively, indicating statistical significant transfer classification on Twitter. We use these classifiers to label the presence of ES and IS in our *Treatment* and *Control* datasets.

Examining Psychosocial Expressions over Time and Language

Next, we describe methods to examine how the COVID-19 pandemic may have caused changes in psychological expressions by comparing our *Treatment* (outbreak year) and *Control* (no-outbreak year) datasets. For both our datasets, we aggregate the number of posts that express symptomatic and support-seeking expressions by day and by type. We compare the pervasiveness of each kind of measure in the datasets, along with conducting statistical significance in their differences using paired t-tests.

Temporal Variation

To compare the daily variation of measures between *Treatment* and *Control* datasets, we transform our data into standardized z-scores. Our datasets rely on the Twitter streaming API, and are subject to daily inconsistencies of available data each day [56]. Transformed z-scores are not sensitive to such absolute values and inconsistencies, and essentially quantify the number of standard deviations by which the value of the raw score is above or below the mean. Similar standardization techniques have been adopted in prior social media time-series studies [33, 57]. z-scores are calculated as $(x-\mu)/\sigma$, where x is the raw value, μ is the mean and σ is the standard deviation of the population. Here, to obtain population μ and σ , in addition to our *Treatment* and *Control* data, we also include year-long Twitter data of over 240M Twitter posts (September 2018 and August 2019). For each of the measures in symptomatic and support-seeking expressions, we calculate the z-score per day and interpret positive z-scores as values above the mean, and negative z-scores as those below the mean.

Linguistic Differences

To examine COVID-19 related linguistic differences in the psychosocial expressions on social media, we employ an unsupervised language modeling technique, the Sparse Additive Generative Model (SAGE) [58]. Given any two datasets, SAGE selects salient keywords by comparing the parameters of two logistically parameterized-multinomial models using a self-tuned regularization parameter to control the tradeoff between frequent and rare keywords. We conduct SAGE to identify distinguishing n -grams ($n=1,2,3$) between the *Treatment* and *Control* datasets, where the SAGE magnitude of an n -gram signals the degree of its "uniqueness" or saliency. SAGE allows us to obtain how the expressions differ during the COVID-19 outbreak as compared to the *Control* period. We conduct two SAGE analyses, one each for symptomatic expressions and support-seeking expressions. For the symptomatic expressions, we first obtain posts that are indicative of either of anxiety, depression, stress, or suicidal ideation in *Treatment* and *Control*, and obtain SAGE for the two datasets. We do similar for support-seeking expressions by obtaining posts that are indicative of either emotional or informational support.

Finally, we cross-examine the salient keywords across symptomatic and support-seeking expressions, to study how concerns are prevalent in either or both of the kinds of expressions. We measure log-likelihood ratios (LLR) along with add-1 smoothing, where LLR close to 0 indicates comparable frequencies, $LLR < 1$ indicates the greater frequency in symptomatic expressions and $LLR > 1$ indicates the greater frequency in support-seeking expressions. Together these linguistic analyses enable us to obtain psychological concerns, and understand how COVID-19 has psychosocially affected individuals, and to contextualize these concerns in the literature on consequences of global crises.

Results

We summarize our first set of results in Table 1. For all our measures, we find statistical significance (as per t -tests) in social media expressions in the *Treatment* data as compared to that in *Control*. Assuming that most other confounders were minimized due to the geo-temporal similarity of the datasets, our findings indicate that the COVID-19 outbreak led to an increase in people's symptomatic and support expressions of mental health. We elaborate on the results below.

Table 1. Comparing social media expressions in *Treatment* (2020) and *Control* (2019) (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

	Treatment (2020)		Control (2019)			
Expression	Mean	Stdev.	Mean	Stdev.	Δ%	t-stat.
Symptomatic Mental Health Expressions						
Anxiety	1.65	0.20	1.35	0.08	21.32	12.31***
Depression	9.00	0.60	8.17	0.35	10.18	10.56***
Stress	19.31	0.77	18.61	0.43	3.76	3.05**
Suicidal Ideation	3.14	0.31	2.62	0.13	19.73	13.46***
Support Expressions						
Emotional Support	8.56	0.84	8.17	0.50	4.77	2.85**
Informational Support	1.75	0.18	1.67	0.08	4.78	3.50***

Temporal Variation

Figure 1 shows the changes in symptomatic mental health expressions for the same period in *Treatment* (2020) and *Control* (2019) years. We find that the *Treatment* and *Control* show significant differences in the people's symptomatic expressions (Table 1), among which, anxiety shows the most significant increase (21.32%), followed by suicidal ideation (19.73%), depression (10.18%), and stress (3.76%). Figure 2 shows the evolution of support-seeking expressions change in the *Treatment* and *Control* datasets. Like above, the differences are significant (Table 1), and we find that not only emotional support increases by 4.77%, and informational support also increases by 4.78%.

In both the plots of Figure 1 and 2, we find a general trend of negative slope (avg. slope = -0.03) within the *Treatment* year, which is closer to zero slope (avg. slope = 3.19×10^{-4}) in the *Control* dataset. This may suggest that within the *Treatment* year, people's mental health expressions gradually leveled out over time, despite the growing rate of COVID-19 active cases. The plots indicate that psychological expressions almost converge at the tails. This could likely be due to people's habituation with the situation and surroundings with the passage of time [59], as has been observed for other crisis events [33, 60]; however, this needs to be explored further. Within the *Control* dataset, we observe a sudden peak on April 28, 2019, which could be attributed to a shooting incident at a synagogue in San Diego [61]. The observations reflect that the COVID-19 pandemic has increased people's mental health expressions on social media, aligning with other contemporary literature and media reports [8, 38].

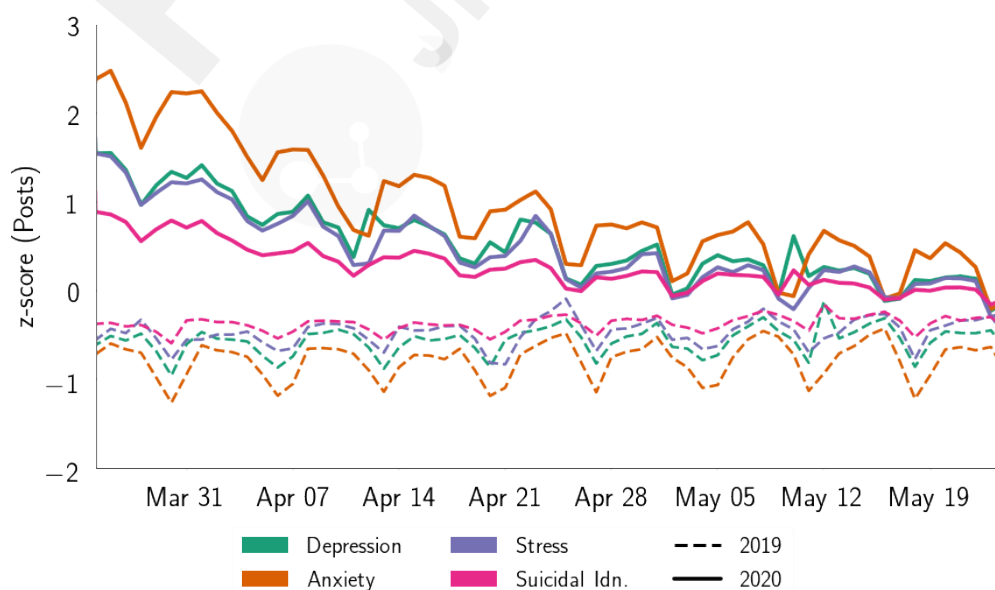


Figure 1. Comparison of symptomatic mental health expressions on social media posts in the same period (March 24 - May 24) in 2019 and 2020 (COVID-19 outbreak year).

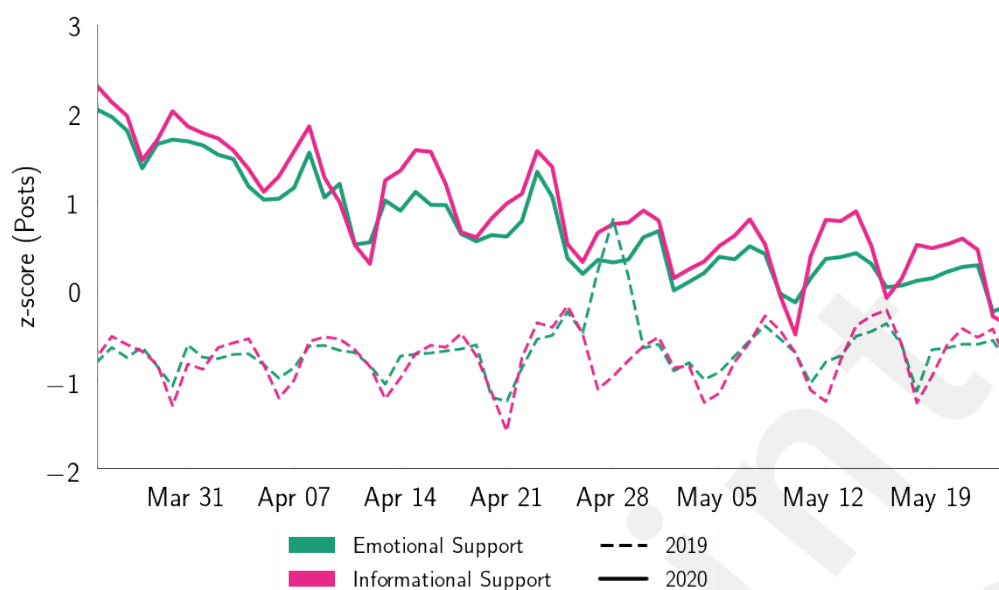


Figure 2. Comparison of support expressions on social media posts in the same period (March 24 - May 24) in 2019 and 2020 (COVID-19 outbreak year).

Linguistic Expressions

Symptomatic Mental Health Expressions

Table 2 summarizes the language differences as per SAGE for posts expressing high mental health expressions in *Treatment* and *Control* periods. A majority of the keywords that occur in the *Treatment* period are contextually related to the COVID-19 pandemic, such as *covid19*, *coronavirus*, *social distancing*, *stayathome isolation*. These keywords are used in posts expressing mental health concerns either explicitly, e.g., “Social distancing is both sad and anxiety-inducing at the same moment”, or implicitly, e.g., “In order to get my family treated, I will do more than beg, and I will donate 25K for research to develop COVID19 vaccine.” We also find that the *Treatment* period uses keywords referring to key personnel such as *dr fauci* (referring to Anthony Fauci, one of the leads in the incumbent White House Coronavirus Task Force in the U.S. and Director of the National Institute of Allergy and Infectious Diseases since 1984 [62]) and political figures like *Nury Martinez* and *Donald Trump*. Further, we find keywords, such as *essential workers*, *doctor jobs*, and *risking lives*, which describe high-risk worker situations, e.g., “I am not complaining about going to work, rather, I am concerned about risking my health for work.”, and certain treatment suggestions that evolved during this period [63] such as *garlic*, *malaria*, and *hydroxychloroquine*, e.g., “I hear a man died after ingesting a malaria drug, though he took a version of the drug used for fish infection”, and “Would eating enough garlic keep me safe from the six-feet away social distancing thing?”

Table 2. Top salient n-grams (n=1,2,3) for symptomatic mental health concerns in *Treatment* and *Control* datasets (SAGE Analysis [58]).

Salient in Treatment (2020)				Salient in Control(2019)			
SAG		SAGE		SAG		SAG	
Keyword	E	Keyword	E	Keyword	E	Keyword	E
covid19	11.17	flattenthecurve	7.44	hospitality	-2.81	tournament	-1.92
lord marvelous	10.87	doctorjobs	7.32	trainee	-2.78	muslim	-1.90
coronavirus	10.58	garlic	7.29	crimes	-2.74	florida	-1.90
social distancing	9.92	hydroxychloroquine	7.28	delay	-2.55	boston	-1.88

nury martinez	9.66	n95 masks	7.26	traffic	-2.55	cashier	-1.87
working councilwoman	9.66	masks gloves	7.26	accident	-2.39	playoffs	-1.86
bored daily	8.69	practice distancing	7.21	finance accounting	-2.26	sales representative	-1.85
stayathome isolation	8.69	physicianjobs	7.13	half finance	-2.22	springfield	-1.84
quarantinelif	8.62	doctorjobs	6.98	auburn	-2.21	border	-1.84
quarantine got	7.87	quarantine life	6.96	half technology	-2.19	barista	-1.77
securityguard	7.63	plz help small	6.96	pete	-2.19	israel	-1.77
essential workers	7.62	small donation	6.92	parttime	-2.18	nc click	-1.76
dr fauci	7.56	stay home orders	6.88	robert half	-2.12	playoff	-1.75
went tired	7.48	self quarantine	6.79	tickets	-2.08	bracket	-1.75
coronaviruspandemic	7.44	positive covid19	6.79	marvel	-2.07	terrorist	-1.65
		risking lives					

Support-Seeking Expressions

Table 3 lists the top keywords as per SAGE for support-seeking posts in *Treatment* and *Control* period. Like above, we find keywords that explicitly relate to COVID-19 occur in the *Treatment* period. We also find that the *Treatment* period consists of posts that seek support related to job and pay such as, *losing jobs*, *need pay*, and *furloughed*, e.g., “Many in our community have lost their jobs, are underinsured and are struggling to make ends meet. Providing pantries, hot meals, hotspots and distance learning opportunities is now more critical than ever, please donate.” Our data also reveals the prevalence of contextually related keywords such as *masks*, *ppe*, *hoarding*, *stockpile*, and *sanitizer* that are medically recommended prevention and containment measures of COVID-19 infection, e.g., “Please contact me if you have any N95 mask or know to obtain some. My sister and a few friend work in the OR and they do not have the supplies to stay safe, they have patients who have #COVID19. TY! #HealthcareHeroes.”

Table 3. Top salient n-grams (n=1,2,3) for support-seeking expressions in *Treatment* and *Control* datasets (SAGE Analysis [58]).

Salient in Treatment (2020)				Salient in Control (2019)			
Keyword	SAGE	Keyword	SAGE	Keyword	SAGE	Keyword	SAGE
lord	7.93	staysafe	4.67	hospitality	-2.86	cashier	-1.79
fauci	6.70	food bills	4.66	duke	-2.51	springfield	-1.79
ventilators	6.59	disinfectant	4.64	shift supervisor	-2.24	delay	-1.76
quarantine	6.47	hand sanitizer	3.08	tampa	-2.21	barista store	-1.76
securityofficer	6.11	clorox	3.03	advisor	-1.95	boston	-1.76
n95	5.53	medical supplies	2.97	customerservice	-1.92	counter	-1.75
hope staying safe	5.36	trying times	2.89	investigation	-1.89	barista	-1.74
ppe	5.25	risking lives	2.87	manager retail	-1.87	columbia	-1.73
wearing masks	5.20	stockpile	2.86	traffic	-1.87	meeting retail	-1.73
uncertain times	5.16	father passed	2.36	muslim	-1.86	informational meeting	-1.73
healthcare workers	5.01	hoarding	2.31	store manager	-1.85	stlouis	-1.72
furloughed	5.00	mask	2.31	tickets	-1.85	marvel	-1.70
asymptomatic	4.95	medical professionals	2.27	playoffs	-1.83	marketing	-1.68
people quarantine	4.90	losing jobs	2.27	cubs	-1.82	server	-1.67
fighting stigma	4.82	toilet paper	2.05	border	-1.81	accident	-1.64

Linguistic Comparability

Finally, Table 4 shows the results of the lexical comparability analysis, where log-likelihood ratios (*LLRs*) demarcate the top keywords used for symptomatic mental health expressions and support-seeking expressions within the *Treatment* dataset. We find that keywords, such as safety precautions (*wear masks*), healthcare and treatment (*health care workers*, *hospitalized*, *beds*, and *icu*), and life/death (*passed away*, *kill people*, *human lives*, and *deaths*) comparably overlap in both kinds of psychological expressions (*LLR*~0). These keywords are also used to raise awareness and express solidarity with healthcare and high-risk workers, e.g., “Taking all safety precautions and adhering to the guidelines established by our health care professionals will keep us safe.” Our lexico-psychological analyses reveal that more clinically relevant keywords and symptoms occur frequently in symptomatic expressions (*LLR*>0), e.g., *sleep schedule* and *tested positive*, whereas, socially relevant and stressful circumstances are more prevalent in support-seeking expressions (*LLR*<0), e.g., *im single parent*, *starve*, and *lost jobs*.

Table 4. Distribution of social media keywords across high symptomatic mental health and support seeking expressions within *Treatment* period using Log-likelihood Ratios (*LLR*). Keywords with *LLR*>0 distinctly occur in high symptomatic expressions, those with <0 distinctly occur in support-seeking expressions, and those ~0 occur comparably in both.

<i>LLR</i>>0		<i>LLR</i>~0		<i>LLR</i><0	
Keyword	<i>LLR</i>	Keyword	<i>LLR</i>	Keyword	<i>LLR</i>
sleep schedule	0.75	infected	-0.01	im single parent	-1
lonely	0.64	wear masks	-0.01	starve	-1
anxiety	0.62	need help	-0.01	meditate	-1
isolation	0.56	kill people	-0.01	sorry loss	-0.73
stay safe	0.56	need pay	0	care people	-0.7
bored	0.56	health care workers	0	hard times	-0.45
tested positive	0.52	passed away	0	people sick	-0.4
quarantine life	0.52	seriousness	0	helping people	-0.4
homeschooling	0.51	human lives	0	sorry hear	-0.39
tired	0.5	deaths	0	urged	-0.33
doctor	0.48	domestic violence	0	new yorkers	-0.29
fighting stigma	0.46	comforting	0	lost jobs	-0.21
depression	0.45	hospitalized	0	hope family	-0.21
stuck inside	0.42	beds	0	selfish	-0.21
sane	0.41	icu	0.01	desperate	-0.21

Discussion

Principal Results

Our study suggests that social media posts during the COVID-19 pandemic contain a significantly higher frequency of symptomatic mental health and support-seeking expressions than a comparable dataset from the same period in the previous year. We also find that they topically relate to the ongoing crisis situation, and include concerns such as: treatment, precautionary measures, loss of jobs, school closings, stockpiling of basic livelihood necessities, feeling lonely, bored, and tired of the restrictions and constraints put on by the ongoing pandemic, and so on. Our findings suggest that although the COVID-19 pandemic has amplified mental health risks and concerns, it may have heightened a sense of belonging and solidarity among individuals — bringing them together, raising collective awareness, and encouraging them to provide support to one another. For example, many people have been considerate about healthcare and essential workers performing high-risk jobs (Instacart delivery workers, Amazon warehouse employees, Uber drivers), and have expressed desire and set up opportunities for donating to those who have lost jobs during the crisis. Media reports

have also indicated how benevolent neighbors have been tending to their elderly neighbors by delivering their groceries and other basic necessities [64].

However, mental health experts say that while the crisis is amplifying risk factors for suicide, the coronavirus outbreak's effect on individuals' mental and emotional wellbeing is complex [65]. Suicide is multifaceted, and while economic loss is a risk factor, so are depression, isolation and fear of the future. At the same time, the crisis is possibly creating a sense of belonging for individuals at risk for suicide as stress and anxiety are normalized, and people come together to better support one another during a crisis [66, 67]. As Florida noted in a recent article [68]: "The long-term toll on mental health of social isolation, remote work, and economic insecurity could have impacts akin to post-traumatic stress disorder; yet, the new focus on mental health may reduce stigma and increase the availability of support services." Indeed, the world beyond the crisis may be one in which mental health is more honestly recognized and supported.

Interestingly, we note that our findings indicate a gradual leveling out of these expressions — both symptomatic and supportive, may reflect a developing 'new normal.' In February 2020, it seemed unthinkable the white-collar workforce of many countries would soon be working solely from home, it seemed unthinkable air travel would plummet by 96%, and all major sporting events will be called off. While the early days of COVID-19 were tainted with feelings of shock, despair, and a sense of lack of control, as shown in our data, over time, many are slowly adapting to a new way of life and coming to terms with the reality that the pandemic is not only here to stay for a while, but might lead to a new world order. Indeed, epidemiologists surmise that many if not most changes surrounding the rhythms of our daily life are likely to fade over time, just as they did after the 1918 influenza epidemic [68]. In other words, the pandemic would make us revisit and possibly reform many of our lifestyle choices and civic roles, and the persistent discussion of the 'new normal' may help bring order to our current turbulence. Others have argued that perhaps the crisis is an prelude to a 'new paradigm,' as recently noted by the World Economic Forum [69]: "Feeling unsettled, destabilized and alone can help us empathize with individuals who have faced systematic exclusions long-ignored by society even before the rise of COVID-19 – thus stimulating urgent action to improve their condition." We should therefore "revel in the discomfort of the current moment to generate a 'new paradigm,' not a 'new normal.' The leveling out trend in our data gives empirical ground to these conjectures.

Nevertheless, if robust anti-viral treatments are developed and rolled out relatively quickly and/or if a vaccine becomes available soon enough, presumably, the changes will be short-lived, and the new normal may be temporary. But if the pandemic comes back in larger waves over the next few seasons, like was the case with historical epidemics, the economic, political, and social crises that have arisen as a consequence will lead to deeper ramifications in turn leading to longer-lasting or permanent changes. Future research will need to explore the persistence of the new normal and the emergence of a possible new paradigm as the pandemic evolves, and therein the mental health impacts further along in the crisis.

Comparison with Prior Work

COVID-19 is not the first pandemic — catastrophic pandemics have been occurring at regular intervals throughout human history, with the 1918 influenza epidemic being the last one before the current pandemic [70]. The backdrop of the 1918 pandemic was that it happened just before the advent of modern psychiatry as a science and a clinical specialty – a time when psychoanalysis was gaining recognition as an established treatment within the medical community [71, 72]. Consequently, psychiatry has had little opportunity to consider such historically important phenomena through its clinical, scientific lens, until now. Although outbreaks of the Zika and Ebola

virus, MERS, and SARS managed to draw global attention, stirring up anxiety and uncertainty in societies, scholars have noted that participation of mental health experts in pandemic preparedness has remained negligible [73]. Consequently, our ability to understand mental health responses as well as the mental health burden in pandemic outbreaks have been limited [74]. For instance, a routinely practiced method of infection control, quarantine and social distancing have received surprisingly little attention in psychiatric literature so far. Baumeister and Leary (1995) [75] contended that humans need frequent contacts, and crisis events further stimulate a need for affiliation and intimacy. Therefore, prolonged isolation and separation from families and their community can have profound effects on individuals even if they are not directly affected by the disease [4]. In the current pandemic, the additional layer of extensive use of social media and exposure to often sensationalized online news, while in physical isolation, may add new complexities to implementing emotional epidemiology in managing concerns, fears, and misconceptions [76], as these tools have been argued to bear negative effects on psychological wellbeing [77, 78].

By adopting social media as a lens to unpack these previously less understood dimensions of a pandemic's mental health effects, our work is one step towards closing some of the above-noted gaps. The published literature posits that the distress and anxiety among individuals in this COVID-19 pandemic may increase the incidence of mental disorders [38, 39, 79]; data thus far from the U.S. point to a population increase in psychological distress of 10% compared to 2018 data [8], a trend which is in line with our present results. These rates may be higher in those regions heavily exposed to COVID-19 or among individuals working during the pandemic, with a recent review reporting over 20% prevalence of anxiety, also consistent with our findings [8].

Prior work found that mental health discourse on Twitter ranges across stigmatizing, inspirational, resource, medical, and social dimensions of expressions [80], and our study revealed similar topical diversity in our dataset. Further, we detected through social media many of the stresses associated with the pandemic – e.g., prolonged isolation, exposure to pandemic-related death, loss of income/career, increased workload, and lack of pertinent and accurate information. These results align with epidemiological findings that COVID-19 has led elevated mental health symptoms for individuals: Nelson et al. (2020) surveyed two thousand individuals from U.S., Canada, and Europe and found elevated symptoms of anxiety and depression compared to historical norms, and observed factors similar to the concerns we detected regarding symptomatic expressions and those related to seeking support. They also reinforce the summary data released by the Crisis Text Line (a major crisis helpline in the U.S.) listing major concerns of crisis support sought during this period [81] — 80% conversations mentioning “*virus*”, 34% mentioning “*anxiety*”, 34% feeling solidarity with friends and family, etc. Along similar lines, there have been numerous reports about the increasing number of mental health crisis helpline calls during this period [82, 83], providing further support and external validation that our social media findings reflect many of the same elements of distress expressed offline during this crisis.

Next, our temporal analyses pointed to a steady decline in people's expressed psychosocial concerns during the two month study period (Figure 1&2), which conforms with similar findings in Google search queries as stay-at-home orders and other COVID-19 related policy changes were implemented in the U.S. [84]. We note contemporary social computing research studying various aspects of the social media discourse related to COVID-19 [48, 85, 86]. By providing complementary evidence to observations by Mackey et al. [85] and Stokes et al. [86] on expressed (mental health) concerns during the crisis, our work further underscores their findings using a comparable (control) dataset, reinforcing and providing empirical credibility to the impression that the COVID-19 pandemic has indeed caused or contributed directly to the mental health concerns that we describe.

Limitations

We note some limitations in our work, many of which present excellent directions for future research. We recognize the lack of transparency related to the Twitter streaming API. Recent research has also questioned the credibility of the “1% Twitter stream” aspect noting that actual sampling data is smaller than what it ideally should have been [56]. Given these data limitations, we decided against conducting several descriptive and fine-grained analyses (such as comparing regions), and refrained from making claims based on comparing absolute numbers of those impacted by various mental health concerns. For example, we cannot define based on our data, whether there were increased or decreased Twitter postings during our COVID-19 study period compared to the same months in 2019. Besides, social media data inherently suffers from biases of self-selection and representation [87], and as a recent article by Chunara and Cook (2020) highlights, public health surveillance (including that for COVID-19) can account for several factors such as the “population at risk” in epidemiology and demographic disparities in the use and behavioral expressions on social media [25].

Further, while we did have data beyond May 24, 2020, we decided to exclude those in order to keep our focus on the effects on social media expressions due to COVID-19 and minimize those that followed the death of George Floyd on May 25, 2020, in the light of the Black Lives Matter protests throughout the U.S. [88]. We also are aware that, with the continuing nature of the pandemic, our conclusions are restricted to the mental health and support-seeking concerns expressed during a finite study period. Events since the end of the study period underscore the dynamic nature of these events, as different parts of the U.S. are heavily affected, while others are recovering and some remain relatively spared. It will be important to extend this work temporarily, increase the size of future samples, and, whenever possible, add geospatial specificity to future analyses. The latter will be especially important for potential supportive interventions locally, if one has the resources and the ability to assemble recurring, near-real-time local “snapshots” as a basis for community focused preventive interventions.

Conclusion

Our work, like those of others studying other major events, further reinforces the potential utility of accessing and analyzing social media data in near-real-time to ‘take the temperature’ of communities. This will require a more focused and robust collection of locally targeted information to build samples that are sufficiently large to produce reliably representative datasets to be useful for public health interventions. Further work is now needed to track mental health-related expressions and those reflecting needs for support throughout the pandemic, which has seen dynamic changes associated with disease spread to areas that had been less affected during the early months of the outbreak. This geospecific research may further enhance our understanding of the causal connections between COVID-spread and waves of expressed distressed. Having the ability to present locally pertinent, contemporaneous analyses offers the opportunity for local public health and mental health providers, as well as political leaders, to develop and deploy targeted support services in a timely fashion.

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Conflicts of Interest

JT receives unrelated research support from Otsuka.

Abbreviations

COVID-19: Coronavirus Disease 2019

API: Application Programming Interface

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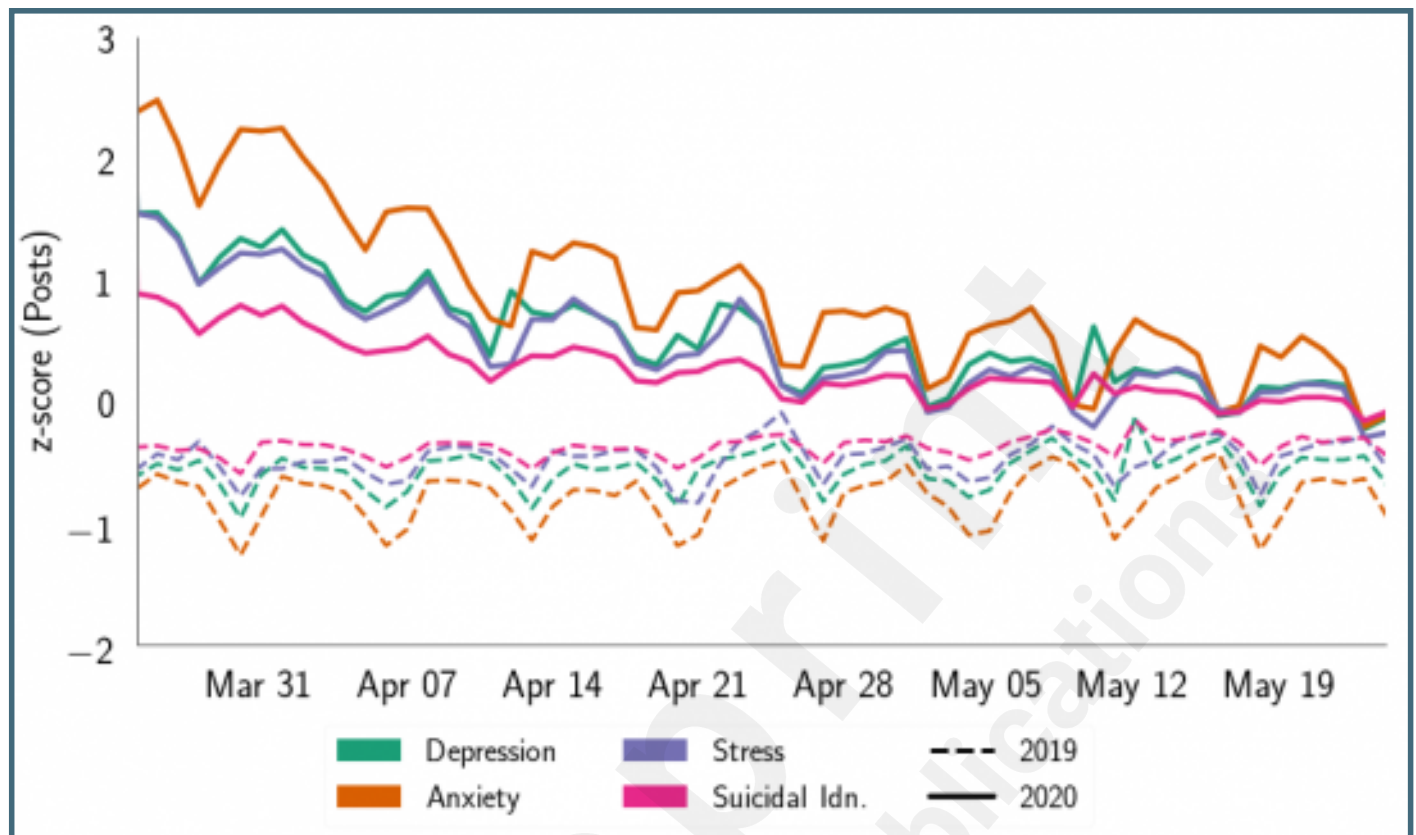
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Supplementary Files

Figures

Comparison of symptomatic mental health expressions on social media posts in the same period (March 24 - May 24) in 2019 and 2020 (COVID-19 outbreak year).



Comparison of support expressions on social media posts in the same period (March 24 - May 24) in 2019 and 2020 (COVID-19 outbreak year).

