Understanding the Impact of COVID-19 on Online Mental Health Forums

LAURA BIESTER, Computer Science & Engineering, University of Michigan

KATIE MATTON, Computer Science & Artificial Intelligence Laboratory, Massachusetts Institute of Technology

JANARTHANAN RAJENDRAN, Computer Science & Engineering, University of Michigan

EMILY MOWER PROVOST, Computer Science & Engineering, University of Michigan

RADA MIHALCEA, Computer Science & Engineering, University of Michigan

Like many of the disasters that have preceded it, the COVID-19 pandemic is likely to have a profound impact on people's mental health. Understanding its impact can inform strategies for mitigating negative consequences. This work seeks to better understand the impacts of COVID-19 on mental health by examining how discussions on mental health subreddits have changed in the three months following the WHO's declaration of a global pandemic. First, the rate at which the pandemic is discussed in each community is quantified. Then, volume of activity is measured in order to determine whether the number of people with mental health concerns has risen, and user interactions are analyzed to determine how they have changed during the pandemic. Finally, the content of the discussions is analyzed. Each of these metrics is considered with respect to a set of control subreddits to better understand if the changes present are specific to mental health subreddits or are representative of Reddit as a whole. There are numerous changes in the three mental health subreddits that we consider, r/Anxiety, r/depression, r/SuicideWatch; there is reduced posting activity in most cases, and there are significant changes in discussion of some topics such as work and anxiety. The results suggest that there is not an overwhelming increase in online mental health support-seeking on Reddit during the pandemic, but that discussion content related to mental health has changed.

CCS Concepts: • **Computing methodologies → Natural language processing**; • **Human-centered computing → Social network analysis**.

Additional Key Words and Phrases: mental health, time series, COVID-19, topic modeling, user interaction

ACM Reference Format:

Laura Biester, Katie Matton, Janarthanan Rajendran, Emily Mower Provost, and Rada Mihalcea. 2021. Understanding the Impact of COVID-19 on Online Mental Health Forums. *ACM Trans. Manag. Inform. Syst.* 1, 1, Article 1 (January 2021), 29 pages. https://doi.org/10.1145/3458770

1 INTRODUCTION

The implications of COVID-19 extend far beyond its immediate physical health effects. Uncertainty and fear surrounding the disease, in addition to a lack of consistent and reliable information, contribute to rising levels of anxiety and stress [58]. Policies designed to help contain the disease also have significant consequences. Social distancing policies and

Authors' addresses: Laura Biester, lbiester@umich.edu, Computer Science & Engineering, University of Michigan; Katie Matton, kmatton@mit.edu, Computer Science & Artificial Intelligence Laboratory, Massachusetts Institute of Technology; Janarthanan Rajendran, rjana@umich.edu, Computer Science & Engineering, University of Michigan; Emily Mower Provost, emilykmp@umich.edu, Computer Science & Engineering, University of Michigan; Rada Mihalcea, rada@umich.edu, Computer Science & Engineering, University of Michigan.

Manuscript submitted to ACM

lockdowns lead to increased feelings of isolation and uncertainty [24]. They have also triggered an economic downturn [70], resulting in soaring unemployment rates and causing many to experience financial stress. Therefore, in addition to the profound effects on physical health around the world, psychologists and psychiatrists have warned that we should also brace for a mental health crisis as a result of the pandemic [19, 48, 58, 67].

Indeed, the literature on the impact of past epidemics indicates that they are associated with a myriad of adverse mental health effects. In a review of studies on the 2002-2003 SARS outbreak, the 2009 H1N1 influenza outbreak, and the 2018 Ebola outbreak, Chew et al. [8] found that anxiety, fear, depression, anger, guilt, grief, and post-traumatic stress were all commonly observed psychological responses. Many of the factors commonly cited for inducing these responses are applicable to COVID-19, including: fear of contracting the disease, a disruption in daily routines, isolation related to being quarantined, uncertainty regarding the disease treatment process and outcomes, the well being of loved ones, and one's economic situation.

While disease outbreaks pose a risk to the mental health of the general population, research suggests that this risk is heightened for those with pre-existing mental health concerns. People who have already experienced mental health disorders are particularly susceptible to experiencing negative mental health consequences during times of social isolation [59]. Further, as Yao et al. [67] warns, they are likely to have a stronger emotional response to the feelings of fear, anxiety, and depression that come along with COVID-19 than the general population.

Given the potential for the COVID-19 outbreak to have devastating consequences for mental health, it is critical that we work to understand its negative psychological effects. In this work, we use Reddit, a popular social media platform, to study how COVID-19 has impacted the behavior of people posting in mental health forums. We focus on three Reddit sub-forums, referred to as subreddits, which are designed to offer peer support for users who are struggling with specific types of mental illness. We aim to determine whether there are changes related to the pandemic in online mental health forums that differ from changes in other online forums. To measure this, we create time series that are representative of the difference between mental health and other (control) forums for a number of metrics, and identify to what extent each metric deviates from expected values during the pandemic.

Our findings include decreased rates of posting in mental health subreddits along with stronger connectivity between users. The content of discussions has become more informational, as users grapple with pandemic-related anxiety and spend less time discussing common issues including work and school. These and other findings provide insights into the specific ways in which COVID-19 has impacted the behavior of users who discuss mental health concerns. These findings can help us understand and potentially alleviate the negative mental health effects of the pandemic; for instance, this type of analysis could help moderators to more effectively support users through future crises. To the best of our knowledge, the method that we propose has not been used previously to study changes in mental health subreddits; previous methods used in these studies have not employed time series analysis in the same way (often just directly comparing observations from two time periods) and therefore do not mitigate the effects of trends and seasonality in the data. The method could also be applied to understand the effects of other major events like political elections and natural disasters.

2 RESEARCH QUESTIONS AND HYPOTHESES

2.1 To what extent is COVID-19 discussed on Reddit?

We expect COVID-19 to be discussed more on mental health subreddits than on the control subreddits, based on prior work indicating that people with existing mental health conditions are likely to have stronger emotional responses during a disaster [59, 67]. Mental health subreddits also focus more on people's lived experiences, strengthening our expectations that discussion will be more prevalent on these subreddits.

2.2 Is COVID-19 leading to increased posting activity in mental health subreddits?

We expect that COVID-19 will have the greatest effect on people with mental health concerns, who post on mental health subreddits more than the general population. We further expect to see increases in posting activity across all subreddits because the virus has led to more time spent online [28]. We therefore hypothesize that although posting behavior will increase across all subreddits (including our control subreddits), the increase will be the greatest in the mental health subreddits.

2.3 Are changes in social interaction patterns during COVID-19 different in mental health subreddits?

As mentioned previously, we expect to see an increase in activity on the mental health subreddits with respect to the control subreddits. We therefore hypothesize that there will be an increase in the number of users who post on the mental health subreddits. We expect to see an increase in the connectivity of users within both the mental health and control subreddits; in other words, we expect that users will interact with a greater number of other users. This hypothesis is motivated by research that has found that seeking social support is a common coping strategy observed during prior disease outbreaks [8].

2.4 Are changes in conversations during COVID-19 different in mental health subreddits?

We hypothesize that due to social distancing regulations and smaller social circles, there will be a decrease in discussion related to travel, and to daily schedules and routines. We expect that the moves to remote school and work will yield a relative increase in discussion of those topics, as they are common stressors for people with mental health conditions in everyday life. Because of a higher reliance on medical treatment including therapy that has moved online, we similarly expect an increase in discussion of treatment as people adjust to new norms. As people with existing mental health concerns are more likely to experience pandemic-related anxiety, we expect a sharper increase in anxiety-related discussion on mental health subreddits.

3 RELATED WORK

3.1 Studying Mental Health via Social Media

In the past decade, social media has emerged as a powerful tool for understanding human behavior, and correspondingly mental health. A growing number of studies have applied computational methods to data collected from social media platforms in order to characterize behavior associated with mental illnesses, and to detect and forecast mental health outcomes (see Chancellor and De Choudhury [6] for a comprehensive review).

Reddit is a particularly well-suited platform for studying mental health due to its semi-anonymous nature, which encourages user honesty and reduces inhibitions associated with self-disclosure [10]. Additionally, Reddit contains subreddits that act as mental health support forums (e.g., r/Anxiety, r/depression, r/SuicideWatch), which enable a more targeted analysis of users experiencing particular mental health conditions. A number of existing works have focused on characterizing patterns of discourse within these mental health communities on Reddit. Studies have analyzed longitudinal trends in topic usage and word choice [5], the relationship between user participation styles and topic usage [16], and the discourse patterns specific to self-disclosure, social support, and anonymous posting [10, 45].

Other studies of Reddit mental health communities have aimed to quantify and forecast changes in user behavior. De Choudhury et al. [12] presented a model for predicting the likelihood that users transition from discussing mental health generally to engaging in suicidal ideation. Li et al. [32] analyzed linguistic style measures associated with increasing vs decreasing participation in mental health subreddits over the course of a year. Kumar et al. [30] examined how posting activity on r/SuicideWatch changes following a celebrity suicide. Our work similarly focuses on analyzing temporal patterns in user activity, but we aim to characterize changes associated with COVID-19.

Beyond Reddit, Twitter has also been used as a platform to study mental health. There is extensive work in this area; one example is Coppersmith et al. [9], who find users who state their mental health-related diagnosis to create groups of users with depression, bipolar disorder, post traumatic stress disorder and seasonal affective disorder. They use language-related features to classify users in each group, and analyze correlations between those features and different disorders. Mitchell et al. [40] similarly classify users based on whether they have reported a schizophrenia diagnosis on Twitter, and analyze the linguistic features that co-occur with schizophrenia.

In addition to analysis focused on the relationship between linguistic measures and mental health, there are a number of studies that have examined social interaction patterns and mental health on social media. For example, De Choudhury et al. [12] analyzed how different user interaction measures, such as the number of posts and comments authored and received, vary between users who do and do not post on r/SuicideWatch. Other existing studies have used similar measures to study the relationship between user interaction patterns and mental health disorders on Twitter [9, 11] and the relationship between user interaction patterns and topic usage on r/depression [16]. Many studies use network analysis methods to measure additional properties of user interactions on social media [11, 55, 61]. Such studies typically create graphs where users are nodes and edges represent interactions between users (e.g., commenting on a Reddit post or re-tweeting a Twitter post). They then characterize social activity by computing metrics such as graph size, density, and clustering coefficient. While some studies analyze per-user interaction patterns by forming a separate graph for each user [11, 55], others use a single social graph to study interactions at the community level [61].

3.2 Mental Health and COVID-19

Since the first cases of COVID-19 were reported in December 2019, there have been a number of studies of its impact on mental health. In a survey of the general public of China during the initial outbreak phase, a majority of respondents perceived the psychological impact of the outbreak to be moderate-to-severe and about one-third reported experiencing moderate-to-severe anxiety [60]. Studies of the impact of COVID-19 among residents of Liaoning Province, China [68] and among the adult Indian population [49] similarly found high rates of anxiety and other types of mental distress.

Wolohan [66] used a classification model to measure prevalence of depression among Reddit users in April 2020; they found that the model predicted higher rates of depression than in previous years, indicating the start of a mental health crisis. Low et al. [33] study fifteen mental health subreddits in the wake of the COVID-19 pandemic. They perform similar analysis to us (focusing specifically on linguistic properties), in particular using LIWC and topic modeling, but use different methods in their analysis and focus on r/COVID_support instead of a broader list of control subreddits.

Our work similarly aims to measure changes in online behavior as a means of understanding the relationship between COVID-19 and mental health. However, we focus on establishing changes in both linguistic and non-linguistic metrics in mental health forums, and study those changes in comparison with a number of control forums. In a preliminary version of this work, we performed similar analysis using only Reddit posts with no control forums and primarily linguistic metrics [2].

3.3 Social Media and COVID-19

More broadly, social media analysis has been used to study impacts of the COVID-19 pandemic and the spread of the virus. Shen et al. [51] used Granger causality tests to show that Weibo posts related to COVID-19 symptoms or a diagnosis could be used to predict case counts up to two weeks ahead of time in China. Ordun et al. [43] explored topics and network features in COVID-19 tweets. They studied the propagation of information related to the pandemic, and showed a relationship between topics and government press briefings. Gencoglu and Gruber [18] created a causal model involving twitter activity and sentiment, COVID-19 statistics, country demographic statistics, and government interventions. They found that country twitter usage, new deaths, new infections, and lockdown announcements all impact COVID-19 related twitter activity.

4 DATA

We collect Reddit posts and comments from January 2017 to May 2020 using the Pushshift[1] monthly dump files and API [1]. We use the monthly dump files that were available during our data collection process (for posts, January 2017 - April 2020; for comments, January 2017 - December 2019) and fill in the later months using the API.[2] We collect data from three mental health subreddits: r/Anxiety, r/depression, and r/SuicideWatch. The reasons for analyzing these three subreddits are twofold: first, over the three-and-a-half years represented in our data, these subreddits have had a significant amount of activity ($\geq$ 25 non-deleted posts every day), making it feasible to treat daily values as a time series. Second, because the subreddits provide support for different mental health disorders, their users may have been affected differently by COVID-19. We separate the data into two time periods: pre-COVID (January 1, 2017 - February 29, 2020) and post-COVID (March 1, 2020 - May 31, 2020), roughly delineating when COVID-19 began to have a serious impact on those in the United States, where the majority of Reddit users are concentrated.[3] This choice of dates was informed by our analysis of the rates at which COVID-19 related words were mentioned in each subreddit (see Section 6.1), which rise sharply near the beginning of March. We choose to focus on the early reaction to the pandemic, but future work could focus on the longer-term effects.

In addition to data from mental health subreddits, we collect data from the same time period for fifty control subreddits, which are chosen using the Python Reddit API Wrapper (PRAW)'s function to select random subreddits; we kept those subreddits with a large percentage[4] of "self-posts," which contain text as opposed to photos, videos, or links to other sites. We also filter out subreddits where the seven-day rolling-mean count of non-deleted content falls below 25 during our data collection period, to ensure that we have sufficient data for time series analysis. While this is less strict than our criteria for considering mental health subreddits (on account of using the rolling mean), we consider the control subreddits collectively (see Section 5.2), so outliers are unlikely to have a strong effect.

In Appendix A we detail how we treated data that was marked as "removed" or "deleted" between posting and collection, and data from the AutoModerator. In Appendix B we list all of the control subreddits. Table 1 shows the average number of daily posts and comments for r/Anxiety, r/depression, r/SuicideWatch, and our control subreddits, along with average character counts.[5] The data extraction is the first piece of our architecture (Figure 1). In our case,

[1] https://pushshift.io/
[2] As with other social media datasets, there may be noise in the form of API changes and data removed after collection. For this reason, we are careful to consider the effects of removed data.
[3] https://www.alexa.com/siteinfo/reddit.com
[4] Defined as $\geq$ 90% in the last 1000 posts in the data collection period
[5] The statistics for 2019 differ from the published version, as the 2019 row was copied from the 2018 row by mistake. The statistics presented here are correct.

Table 1. Mean number of posts (P) and comments (C) per day across the three subreddits in our dataset, and mean posts and comments per day across control subreddits with each subreddit weighted equally. The final row gives the mean daily character counts for posts and comments, with each day and subreddit weighted equally.

	r/Anxiety		r/depression		r/SuicideWatch		Control	
	P	C	P	C	P	C	P	C
2017	121	514	397	1707	131	705	220	1706
2018	175	729	510	2027	204	1055	282	2374
2019	218	817	674	2398	295	1396	394	2972
2020	253	1146	695	2222	392	1691	456	3094
Characters	915	302	982	268	1012	264	726	248

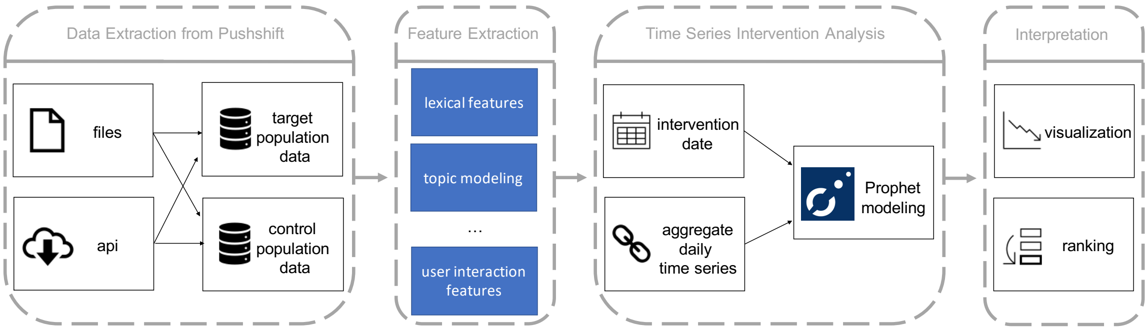


Fig. 1. Architecture of our system. We start by extracting data from our target (mental health) and control populations. We then extract linguistic and network features and perform time series intervention analysis. Finally, we interpret the features by visualizing the comparison between each time series and the expected value, and by ranking the results by number of outliers.

the mental health subreddit data makes up the "target population data," while the control subreddit data makes up the "control population data."

5 METHODOLOGY

Our goal is to identify how mental health subreddit activity has changed during the pandemic, in ways that differ from activity changes on Reddit overall. To this end, we create time series of metrics (Section 5.1) encompassing activity levels, user interactions, and text content. We compute the difference between mental health and control subreddits (Section 5.2). Finally, we use a time series intervention analysis technique to determine whether there are significant changes in our metrics during the pandemic (Section 5.3). The code used in this project is publicly available.[6]

5.1 Reddit Activity Metrics

We begin by creating a lexicon of words that are commonly used to refer to COVID-19. This allows us to determine the extent to which users in each subreddit are discussing COVID-19, and also gives us a clearer idea of when COVID-19 begins to directly affect discussion on the mental health subreddits. We base the lexicon on fifteen twitter search keywords from Huang et al. [23], and add six additional words that we believe are indicative of discussion about

[6]https://lit.eecs.umich.edu/downloads.html#COVID-19%20Mental%20Health%20Effects

COVID-19. The full lexicon is listed in Table 2. We convert to lowercase when counting occurrences, and therefore exclude duplicate terms that only differ in their case.

To study changes in the amount of mental health subreddit activity (a proxy for the amount of support needed by users), we compute the post and comment counts for each day; we include deleted posts, as we believe the act of posting indicates some mental health concern from the user.

Next, we seek to study changes in social interaction patterns on each subreddit. To do this, we define a set of user interaction measures, which were inspired by prior work on network analysis applied to social media [26, 56, 64, 65]. To obtain these measures, we start by forming social graphs based on subreddit activity patterns. For each day and subreddit, we consider each unique user who authored a post or comment to be a node in the graph. We add an undirected edge between each pair of users who "interacted" at least once, where we consider an "interaction" to be commenting on another user's post or comment. We then compute nine metrics commonly used to characterize graphs as our *user interaction measures*, which are described in detail in Table 3. We use the NetworkX library [21] to assist with graph creation and metric extraction.

Finally, to study changes in discussion content that occur during the pandemic, we use the Linguistic Inquiry and Word Count (LIWC) lexicon [46] and Latent Dirichlet Allocation (LDA) topic modeling [3]. The LIWC lexicon consists of seventy-three hierarchical psycholinguistic word categories, encapsulating properties including linguistic categories (e.g., 1st person plural pronouns, verbs), emotions (e.g., anxiety, sadness), time (e.g., present, future), and personal

Table 2. Our lexicon of COVID-19 terms.

Original Search Terms				Additional Terms	
2019-ncov	COVID	mers	SARSCOV19	corona	rona
2019ncov	COVID-19	sars	wuflu	outbreak	sars-cov-2
coronavirus	COVID19	SARS2	Wuhan	pandemic	virus

Table 3. Names and descriptions of user interaction measures.

Metric Name	Description
Node Count $\|N\|$	Number of unique users who posted or commented
Edge Count $\|E\|$	Number of unique users who interacted through a reply to a post or comment
Density $\frac{2\|E\|}{\|N\|(\|N\|-1)}$	Number of edges in graph over number of possible edges
Connected Component Count	Number of subgraphs in which all pairs of nodes are connected by an edge
Mean Connected Component Size	Mean number of nodes in a connected component
Mean Shortest Path	Mean distance between each pair of vertices that are connected by a path
Diameter	Maximum distance between any pair of nodes within a connected component
Clustering Coefficient	Measure of the degree to which nodes tend to cluster together; Computed as in [62]
Assortativity	Measure of the tendency of nodes with similar degrees to attach to each other (see Eq. 21 in [42])

concerns (e.g., work, money, death). During its creation, it was validated by multiple judges [46], and it has been used extensively in related work [9–11, 15, 30, 32, 40, 45]. To capture the discussion topics that are common within r/Anxiety, r/depression, and r/SuicideWatch specifically, we train a single topic model on posts from these three subreddits. This provides us with a set of topics, where each topic is defined as a distribution over words. We use this trained model to infer topic distributions for both the mental health and the control subreddit data. This enables us to analyze changes in the same mental health related topics within both sets of communities. We ensure that discussions from each of the mental health subreddits are equally represented in our training dataset by randomly downsampling the posts from the subreddits with more data. We use the implementation of LDA topic modeling provided in the MALLET toolkit [35] and train models with $k = 5, 10, .., 40$ topics. We select a single model to use in our analysis by examining their coherence scores, a measure of the semantic similarity of high probability words within each topic [38]. As coherence tends to increase with increasing k, we select k as the first local maxima of coherence scores, which we found to be $k = 25$.

In Appendix C, we show the 25 topics obtained from our topic model, along with the highest probability words associated with each topic. We also provide labels that summarize the essence of each topic, which we create by examining their representative words. Common themes of discussion include daily life concerns (e.g., school, work, sleep and routine), personal relationships (e.g., friends, family, relationships), and mental health struggles (e.g., anxiety, suicide and death, medical treatment). There was one topic for which the keywords did not have a clear interpretation (see the '-' entry in Appendix C); we did not include this topic in our analysis.

When using text content, we remove special characters and sequences, such as newlines, quotes, emails, and tables. To represent the text of a post, we concatenate the title with the text content, as was done in prior work [5]. We apply additional pre-processing steps for our topic modeling analysis: (1) we remove a set of common stopwords, excluding words that appear in the LIWC dictionary from this set as they have been found to have psychological meaning, (2) we form bigrams from pairs of words that commonly appear together, and (3) we lemmatize each word.

The extraction of these metrics makes up the second piece of our architecture (Figure 1). In the analysis that follows, we compute each of the activity metrics mentioned for each day and each subreddit. We aggregate post-level measures by taking the mean value across all posts created on a given day. This provides us with a daily time series for each metric and each subreddit.

5.2 Establishing and Accounting for a Control Group

In this work, we want to compare changes in mental health subreddits to changes that have happened more broadly on Reddit, in what we define as our control group. Our control group consists of the fifty control subreddits described in Section 4. Subreddits that are not dedicated to mental health have similarly been used as controls in prior work [25, 52].

For each of our Reddit activity metrics (Section 5.1), we form a single "control" time series by aggregating the individual series of each of the control subreddits. We first apply z-normalization to each of the time series for each subreddit r using the mean and standard deviation from the pre-COVID period; this gives us the normalized series s_r^{norm}. Normalization is necessary because it ensures that changes in each subreddit will be on a similar scale. We then form a single "control" series by taking the mean of these normalized series.

For each of our mental health time series, we similarly apply normalization, so that they on are the same scale as the control series. We examine how the mental health subreddits have changed with respect to the control subreddits by computing the difference between the mental health time series and the control time series for each metric at each timestep. This difference d_{mh} is computed separately for each mental health subreddit mh, and is the metric used in our time series analysis.

$$d_{mh} = s_{mh}^{norm} - \sum_{c \in control} s_c^{norm} \cdot \frac{1}{|control|} \tag{1}$$

5.3 Time Series Analysis

We treat the task of identifying changes in subreddit activity patterns as a time series intervention analysis problem. We contrast this approach with an approach in prior work [30] that examines the impact of an event on activity within mental health subreddits. In this approach, a t-test is used to compare the observations from "before" and "after" a meaningful event. This treatment ignores the effects of seasonality and longer-term trends, which is possible because the periods surrounding the event are only two weeks. However, we observe both strong trends over time and seasonal components in our data, making a direct comparison of the COVID-19 period with any other period using a t-test unreliable. Instead, we: (1) fit a time series model to the pre-COVID observations for each of the metrics described above and then (2) examine how the values forecasted by the model compare to the observed values during the post-COVID time period.

We smooth each time series and remove day-of-week related fluctuations by computing a seven-day rolling mean over the time series. We use the Prophet model [57] to create a model of the period before COVID-19. This model was initially created by Facebook to forecast time series on their platform, such as the number of events created per day or the number of active users. We find that our time series, also compiled from social media, have many similar properties.

The Prophet model is an additive regression model with three components:

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \tag{2}$$

The trend is encapsulated by $g(t)$, a piecewise linear model. The seasonality of the data is captured by $s(t)$, which is approximated using a Fourier series. Since we smooth our data on a weekly basis, we use only yearly seasonality, excluding the optional weekly and daily seasonality components. The third term, $h(t)$, represents holidays. We find that adding a list of US holiday dates reduces error for most of our time series in the pre-COVID period, likely because the Reddit population is centered in the United States. Finally, ϵ_t represents the error, in this case fluctuations in the time series that are not captured by the model.

Some alternatives to the Prophet model are Seasonal Autoregressive Integrated Moving Average (SARIMA) [4] and Long Short-Term Memory (LSTM) [22]. We chose Prophet over SARIMA because our data is non-stationary, and stationarity is a requirement for the ARIMA class of models. Similarly, while we may have been able to fit our data using a LSTM model, we found that in practice Prophet worked quite well and offered useful built-in features such as adding holiday dates as variables.

After training the model on the pre-COVID data, we predict values for the post-COVID period. The model computes uncertainty intervals over the predicted values by simulating ways in which the trend may change during the period of the forecast; we use this method to compute the 95% prediction interval. Our null hypothesis is that there has been no change in trend; in this case, we would expect 5% of the data in the post-COVID period to fall outside of the prediction interval. Our alternate hypothesis is that there was a change in the trend of the time series (which may be attributable to COVID-19); in this case, more than 5% of the data in the post-COVID period will fall outside of the prediction interval.

We apply a one-sample proportion test to assess whether the proportion of observations outside of the prediction interval in the post-COVID period is significantly greater than 5%; the details of this test are in Appendix D. The time series analysis makes up the third piece of our architecture (Figure 1).

6 FINDINGS

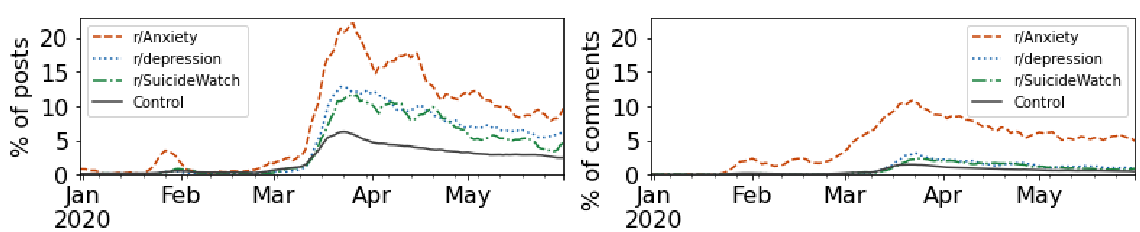
6.1 To what extent is COVID-19 discussed on Reddit?

We want to determine how much discussion on various subreddits focuses on COVID-19, as we believe this measure will relate to the extent to which COVID-19 will impact our other metrics. In turn, this is also an indication of how pre-occupied users are with the pandemic. Using our COVID-19 lexicon (Section 5.1), we compute the percentage of posts and comments per day that mention any words related to COVID-19.

Results. The results are shown in Figure 2. We see that COVID-19 is discussed across all three mental health subreddits, and our control subreddits. Furthermore, we see that COVID-19 discussion is more prevalent on all mental health subreddits than on our control subreddits. Additionally, it is discussed far more on r/Anxiety than the other mental health subreddits, and far earlier, with some discussion in late January, when reports of lockdowns in China first appeared in the news.

Discussion. It is interesting to note that a higher percentage of posts mention COVID-19 than comments; we believe that this is because comments do not need to explicitly mention the virus when it is already an established conversation topic. We note that COVID-19 discussion is more prevalent on all mental health subreddits than our control subreddits. The more prevalent COVID-19 discussion on mental health subreddits compared to the control subreddits makes us expect larger effects of COVID-19 on mental health subreddits than on the controls. The aforementioned higher rate of COVID-19 discussion on r/Anxiety compared to the other subreddits, along with the early discussion in January, hints that the overall effect of COVID-19 on all of our metrics may be the strongest on r/Anxiety.

When choosing the date to consider as the beginning of the post-COVID period in our time series analysis, we considered March 1st, 2020 as a sensible date, as it aligns with the period during which the United States (where the majority of Reddit users reside) began to take COVID-19 seriously. March 1st directly follows the first announced US COVID-19 death on February 28th, and preceded school closures and state lockdowns. Our analysis also shows that discussion of COVID-19 on mental health and control subreddits began to increase in the beginning of March, as the virus began to have a significant impact on people's lives.



(a) Post

(b) Comment

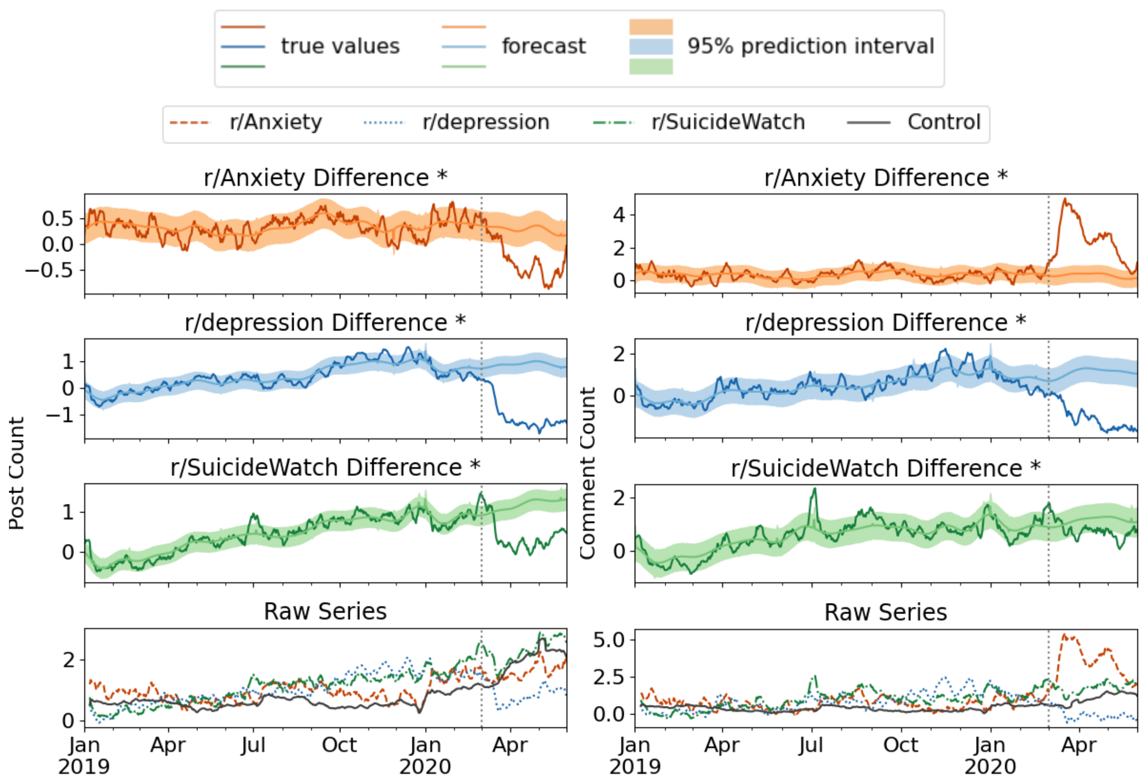
Fig. 2. Percentage of posts and comments per day mentioning COVID-19 related words across mental health and control (averaged) subreddits.

6.2 Is COVID-19 leading to increased posting activity in mental health subreddits?

To discover whether there have been increased mental health concerns as a result of the pandemic, we look at the difference between normalized daily post and comment counts in each mental health subreddit and our control subreddits.

Results. Figure 3 shows the predicted versus the actual post count difference for the three subreddits when compared to the controls. We note that generally, the number of daily posts and comments in mental health subreddits decrease in comparison to those in the control subreddits, with the exception of comments on r/Anxiety where we observe an increase.

Discussion. The results suggest that contrary to our hypothesis, increased mental health concerns are not causing a rise in activity on those forums, beyond the overall rise in activity. We observe a decrease in many cases, although for posts on r/Anxiety and r/SuicideWatch, levels of activity eventually rise to be near the predicted values. The most notable change is the sharp increase in comments on r/Anxiety; this is even more notable given the fairly steady number of



(a) Post Count

(b) Comment Count

Fig. 3. Daily post and comment count differences over time. The lighter line is the Prophet forecast, the shaded area is the 95% prediction interval, and the darker line is the true value. Subreddits marked with * have a statistically significant percentage of outliers (with Bonferroni correction; $\alpha = 0.05$ before correction).

posts in the raw series. We believe that this is a side-effect of the moderation policy that was implemented on r/Anxiety during the pandemic; users were asked to share thoughts about the pandemic on a “COVID-19 megathread.” Multiple megathreads on the subreddit contain $> 10,000$ comments, yielding notable changes for many metrics encompassing comments on r/Anxiety, while posts are less affected. The activity rate in these megathreads supports prior work showing that epidemics often lead to increased anxiety rates [58].

Our original hypothesis was that daily activity would increase more rapidly on mental health subreddits than controls during what is likely to be a COVID-19 related mental health crisis; however, this relies on the simplistic assumption that an increase in mental health symptoms would lead to an increase in mental health posts. Given that depression can cause people to socially withdraw [34], the notable reduction in post volume on r/depression could be consistent with prior work which found that depressive symptoms are common during pandemics [8]. Research also indicates that delayed depression is a common symptom trajectory following disaster events [41, 47]; therefore, future work could look at the longer-term trends following the onset of the pandemic.

6.3 Are changes in social interaction patterns during COVID-19 different in mental health subreddits?

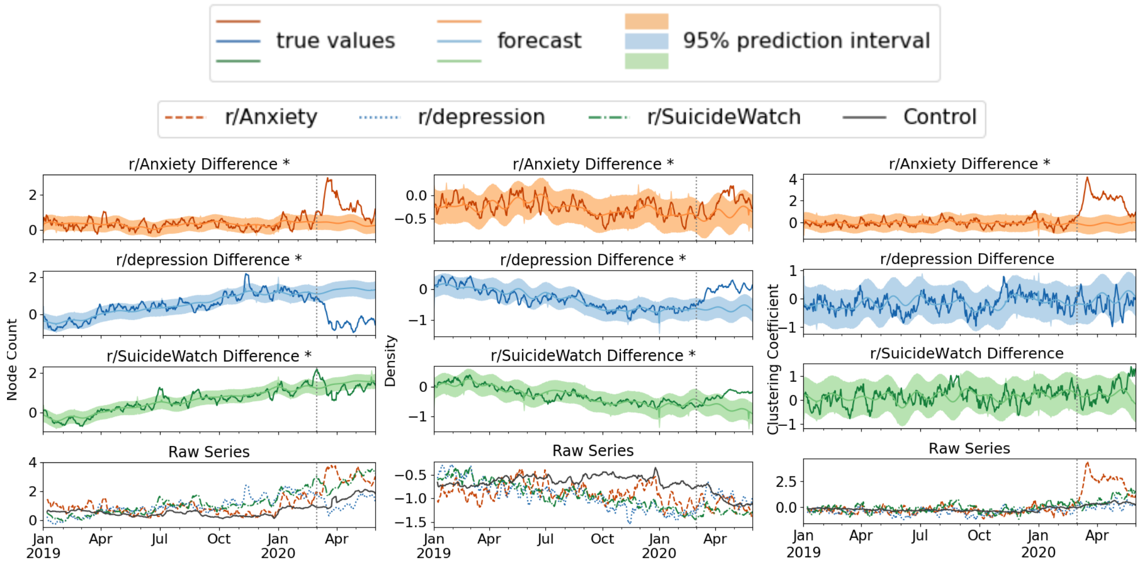
We next examine how patterns in social interaction change in mental health subreddits with respect to control subreddits during COVID-19. We quantify social interaction using *user interaction measures*, which are derived from a graph representing daily user interactions. As with our analysis of activity levels, for each of these measures, we examine changes that occur during the COVID-19 pandemic by computing the proportion of outliers produced by our forecasting model (see Section 5.3).

Results. We present the metrics for which we observe a significant change in the difference between the mental health subreddits and the control subreddits in Table 4. We observe the greatest number of significant changes on r/Anxiety; changes in 8 out of the 9 metrics we investigated are significant.

We see a notable rise in the number of nodes (Node Count) on r/Anxiety (Figure 4a); this increase is significant even given the observed increase in the number of nodes in the control subreddits (see the “Raw Series” plot). On the other hand, we observe a significant decrease in Node Count on r/depression. We also see significant changes in Node Count on r/SuicideWatch. There is an initial spike that occurs at the start of the post-Covid period, and then the values drop below expectation.

Table 4. User interaction metrics with a significant percentage of outliers (with Bonferroni correction; $\alpha = 0.05$ before correction) in each subreddit. Arrows mark the direction in which the mean of the outliers shifted from the predicted mean.

r/Anxiety			r/depression			r/SuicideWatch		
Topic	% Outliers		Topic	% Outliers		Topic	% Outliers	
Edge Count	100	↑	Node Count	95	↓	Connected Component Count	87	↓
Clustering Coefficient	90	↑	Connected Component Count	91	↓	Node Count	59	↓
Node Count	88	↑	Edge Count	86	↓	Density	53	↑
Assortativity	50	↑	Density	86	↑	Edge Count	45	↑
Mean Connected Component Size	50	↑	Mean Connected Component Size	33	↓	Mean Connected Component Size	32	↑
Mean Shortest Path	33	↑						
Density	28	↑						
Connected Component Count	26	↓						



(a) Node Count (b) Density (c) Clustering Coefficient

Fig. 4. Average daily difference in user interaction metrics across comments from a selection topics over time. The lighter line is the Prophet forecast, the shaded area is the 95% prediction interval, and the darker line is the true value. Subreddits marked with * have a statistically significant percentage of outliers (with Bonferroni correction; $\alpha = 0.05$ before correction).

On r/depression and r/SuicideWatch, we observe a significant increase in graph Density (Figure 4b) and a significant decrease in connected component count (Table 4). We do not observe a significant change in the graph Clustering Coefficient on either r/depression or r/SuicideWatch (Figure 4c).

Discussion. All of the measures that we investigated, excluding Node Count, in some way capture graph connectivity. On r/Anxiety, the direction of change in the metrics consistently indicates an increase in connectivity. The observed changes were likely influenced by the creation of the COVID-19 megathreads, which subsume the content of what would typically be many separate threads. In the user graph, this has the effect of creating links between users that otherwise wouldn't exist, thereby increasing the connectivity of the graph.

Node Count is effectively a measure of the number of unique users who post or comment on a subreddit each day, and therefore should not be directly affected by the existence of COVID-19 megathreads. The increase in the number of nodes on the control subreddits suggests that COVID-19 has led more people to post on Reddit in general, and the even larger increase on r/Anxiety suggests that the pandemic has led people to use Reddit to discuss anxiety related concerns to an event greater extent. This finding is aligned with prior work that has found that epidemics often lead to increased rates of anxiety [58]. As discussed in Section 6.2, we hypothesized that activity in each of the mental health subreddits would *increase* compared to the control subreddits, so we find the result of significant decrease in Node Count on r/depression surprising. In future work, it would be interesting to examine the factors driving this trend and the extent to which it is upheld as we move further past the initial onset of the pandemic.

While they are prevalent on r/Anxiety, there are no COVID-19 megathreads on r/depression and r/SuicideWatch. Therefore, the observed increase in graph Density and decrease in Connected Component Count, which both indicate an increase in graph connectivity, likely reflect a genuine increase in the connectedness of users. Although we saw a decrease in the *number* of unique users posting in each of these subreddits, the increase in connectivity measures suggests that those users who *are* posting have increased their levels of interaction with other users. This may reflect an increase in mental health related concerns for these users, which would be consistent with prior work pointing to the particularly severe mental health effects of pandemics for those with pre-existing mental health disorders [59, 67]. However, the increase in connectivity also has some positive implications; the literature on epidemics indicates that seeking social support is an important coping strategy [8, 68]. Therefore, users may be better able to handle the stress of the pandemic as a result of the increase in interaction. It is worth noting that although we see an increase in graph Density, we do not observe a significant change in the graph Clustering Coefficient on either r/depression or r/SuicideWatch. This aligns with our text content analysis (see Section 6.4), in which we observe an increased sense of community and togetherness; here, we see that users have increased their interaction with other users in a rather indiscriminate manner, as opposed to forming increasingly tight-knit groups that interact primarily with each other.

6.4 Are changes in conversations during COVID-19 different in mental health subreddits?

We look at the difference between mental health and control subreddit discussion using two types of features: LIWC categories and topics obtained from an LDA model. The LIWC features give us a sense of changes in common language dimensions, while the LDA-derived topics allow us to explore areas of discussion that are typically of concern in the mental health subreddits. There is overlap between LIWC categories and some topics, such as Death, Family, and Anxiety, although the results may not match perfectly as the models are defined differently. For each of the metrics, we examine changes that have occurred since COVID-19 by computing the proportion of outliers produced by our forecasting model (see Section 5.3) in the post-COVID period. We wish to see if mental health discussions (likely discussion between users who have a mental health disorder) have changed in different ways than discussions on other forums.

6.4.1 LIWC Analysis.

Results. In our LIWC analysis, we analyze both posts and comments. Table 5 shows the categories with the most outliers; Figures 5 and 6 show time series for particular categories for each subreddit for posts and comments, respectively. We see notable changes across a number of categories. While some changes are consistent across subreddits and between posts and comments, others are not; in particular, we see more drastic changes in r/Anxiety comments when compared with the control comments than in any other category of discussion, and we see that changes on r/Anxiety are often different than those on the other subreddits. When analyzing posts, we see across the mental health subreddits that there are differences in categories related to *action*. We see significant drops in the Motion category (Figure 5b) on r/Anxiety and r/depression; in contrast, the presence of words in this category are fairly consistent across our control subreddits. We also see significant decreases in verb usage on r/Anxiety and r/depression (Figure 5a), whereas verbs increase slightly on the control subreddits.

In the control subreddit posts, prevalence of words in the Work category remained fairly constant, while discussion of Work decreased across the three mental health subreddits, especially on r/Anxiety (Figure 5c; see the grey line in the “Raw Series” plot for the control subreddit trend). On the other hand, we see a large uptick in discussion of the Money category in r/Anxiety comments (Figure 6a). This change only takes place on r/Anxiety; we observe a reduction in both the Work and Money categories on r/depression and r/SuicideWatch.

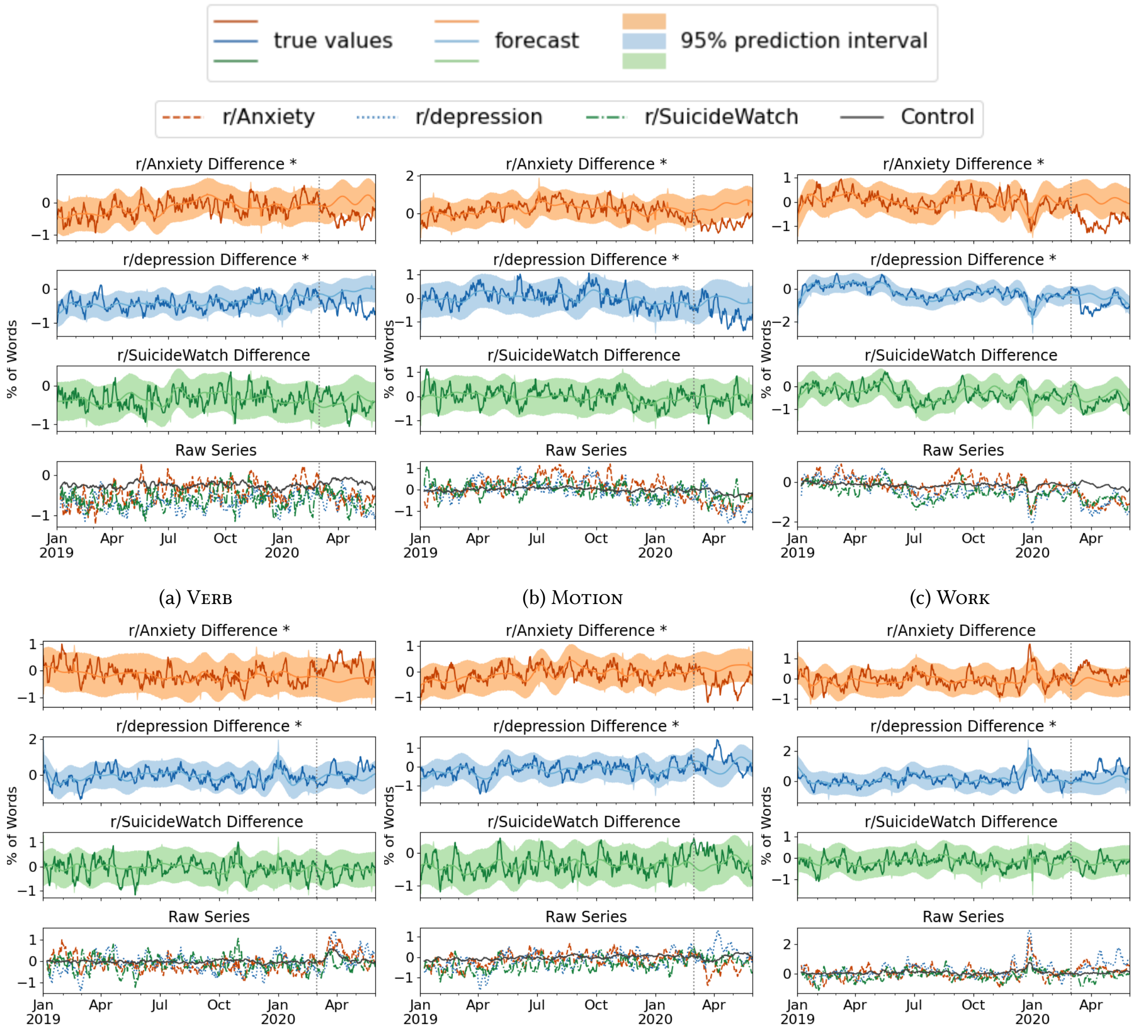
Table 5. Ten LIWC categories with the highest proportion of outliers in each subreddit for posts and comments. Arrows mark the direction in which the mean of the outliers shifted from the predicted mean. Categories marked with * have a statistically significant percentage of outliers (with Bonferroni correction; $\alpha = 0.05$ before correction).

	r/Anxiety			r/depression			r/SuicideWatch		
	LIWC Category	% Outliers		LIWC Category	% Outliers		LIWC Category	% Outliers	
Posts	Work*	83	↓	FocusPresent*	66	↓	NegEmo*	29	↑
	Motion*	73	↓	Verb*	53	↓	Leisure*	23	↓
	Body*	52	↑	Pronoun*	42	↑	FocusPast*	22	↑
	Verb*	47	↓	I*	39	↑	Hear	16	↑
	Bio*	38	↑	Feel*	39	↓	I	15	↑
	Feel*	38	↑	Motion*	36	↓	NetSpeak	15	↑
	I*	36	↓	Work*	35	↓	FocusFuture	14	↓
	Drives*	35	↓	Family*	33	↑	FocusPresent	13	↑
	PPron*	35	↓	Death*	33	↑	Feel	13	↓
	AuxVerb*	34	↓	PPron*	32	↑	Assent	13	↓
Comments	Achiev*	100	↓	Discrep*	60	↑	Conj*	34	↑
	We*	99	↑	Bio*	38	↓	Drives*	29	↓
	Article*	98	↑	Relativ*	38	↓	Affiliation*	29	↓
	PPron*	98	↓	Prep*	36	↑	Work*	27	↓
	Pronoun*	97	↓	Social*	33	↑	Relativ*	27	↓
	FocusPresent*	97	↓	Pronoun*	32	↑	Verb*	26	↓
	Space*	96	↑	Cause*	28	↑	Time*	25	↓
	I*	95	↓	Body*	28	↓	Anger*	22	↑
	Death*	93	↑	Insight*	28	↑	Bio*	22	↑
	Verb*	91	↓	Time*	28	↓	Assent*	21	↓

Changes in pronoun usage occur on all of the subreddits; we see an increase in the We category with respect to our control subreddits (Figure 5d for posts; Figure 6b for comments). There are less consistent changes in the usage of pronouns other than We; there is a significant increase in I in r/depression posts, while there is a significant *decrease* on r/Anxiety (Figure 5e).

Discussion. The fact that changes in comments on r/Anxiety dwarf the changes in posts is likely due to the COVID-19 megathreads that move much of the virus-related discussion to the comments section. While we expect that people across the subreddits are similarly constrained in terms of motion, the relative decrease in the Motion category indicates that those with anxiety disorders may be somewhat more adherent to lockdown procedures. This decrease is potentially concerning, as physical activity has been associated with positive mental health effects [54].

While we hypothesized that people losing their jobs and adjusting to remote work would cause an uptick in work-related discussion, we observe the opposite. The lack of direct conversation about work indicates that there may have been a decrease in work-related stressors, which can increase anxiety and depression [7, 37], or that these stressors may have become secondary to other concerns. However, the large uptick in discussion of the Money category in r/Anxiety comments indicates that there *is* concern among those with anxiety disorders about their economic position during the pandemic, despite the fact that these conversations may not directly relate to work. The decrease in both the Work and



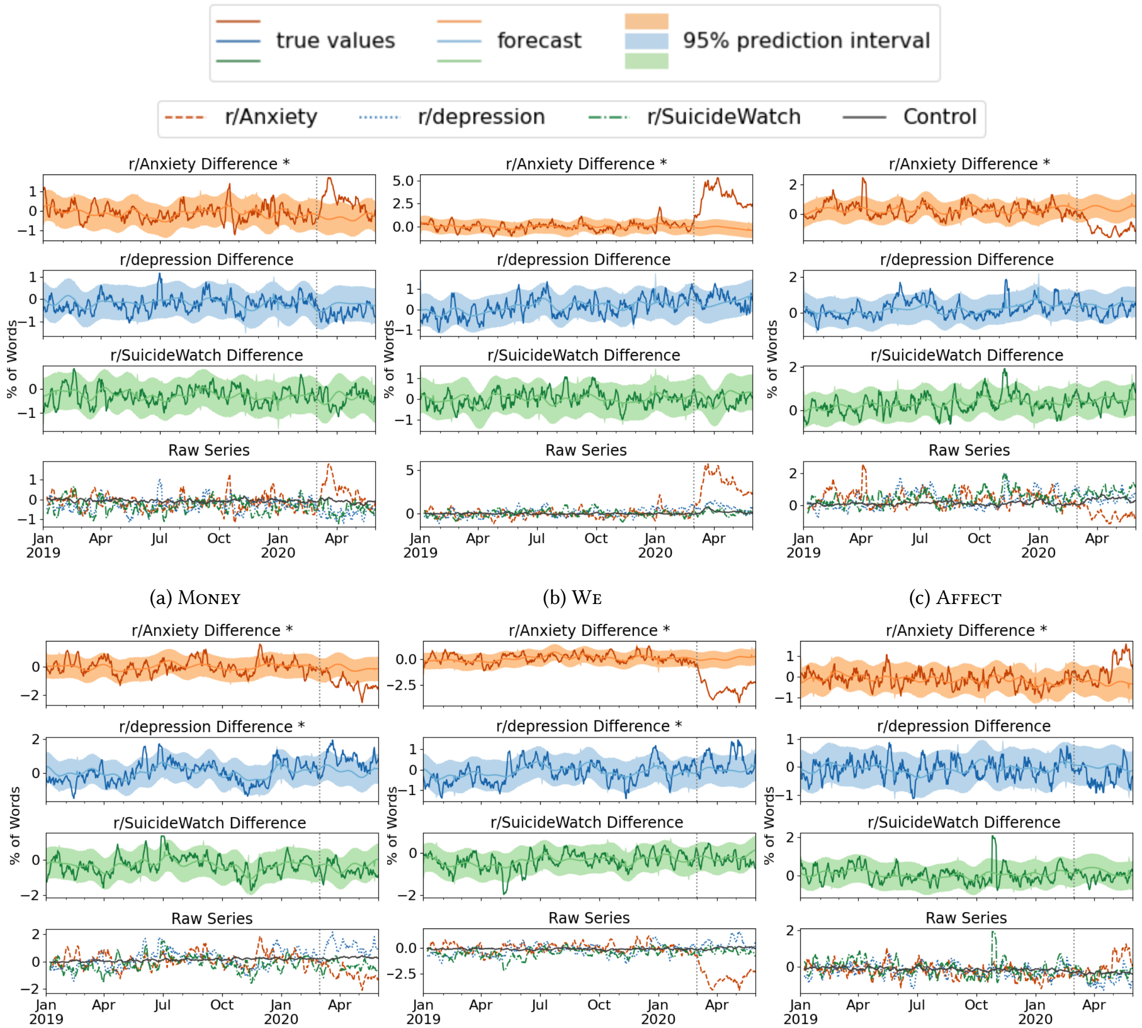
(a) Verb (b) Motion (c) Work

(d) We (e) I (f) Family

Fig. 5. Average daily difference in percentage of words (normalized) across posts from a selection LIWC categories over time. The lighter line is the Prophet forecast, the shaded area is the 95% prediction interval, and the darker line is the true value. The final subplot shows the raw series for the individual mental health subreddits and for the average of the controls. Subreddits marked with * have a statistically significant percentage of outliers (with Bonferroni correction; $\alpha = 0.05$ before correction).

Money categories on r/depression and r/SuicideWatch indicates that the economic concerns caused by the pandemic may more strongly affect those with anxiety disorders.

The increase in the We category with respect to our control subreddits indicates an increased feeling of togetherness and community in mental health subreddits, and it is especially meaningful to see a significant relative increase on r/Anxiety and r/depression given that the control subreddits also have an increase in words in the We category. Social connection has been shown to be an important coping mechanism for people's mental well-being during the pandemic



(a) Money (b) We (c) Affect

(d) Social (e) Pron (f) Number

Fig. 6. Average daily difference in percentage of words (normalized) across comments from a selection LIWC categories over time. The lighter line is the Prophet forecast, the shaded area is the 95% prediction interval, and the darker line is the true value. The final subplot shows the raw series for the individual mental health subreddits and for the average of the controls. Subreddits marked with * have a statistically significant percentage of outliers (with Bonferroni correction; $\alpha = 0.05$ before correction).

[8, 68], which makes the increased feeling of togetherness in mental health forums encouraging. This positivity may come as the result of the “honeymoon phase” that occurs in the wake of disasters; in this phase, there is significant support surrounding the disaster, and the community bonds over shared experience [13]. Direct references to some social connections also increase, in the form of mentions of Family (Figure 5f). It is important to note that our analysis is not able to determine if mentions of family are in relation to increased support or stress, which could be interesting to study in future work.

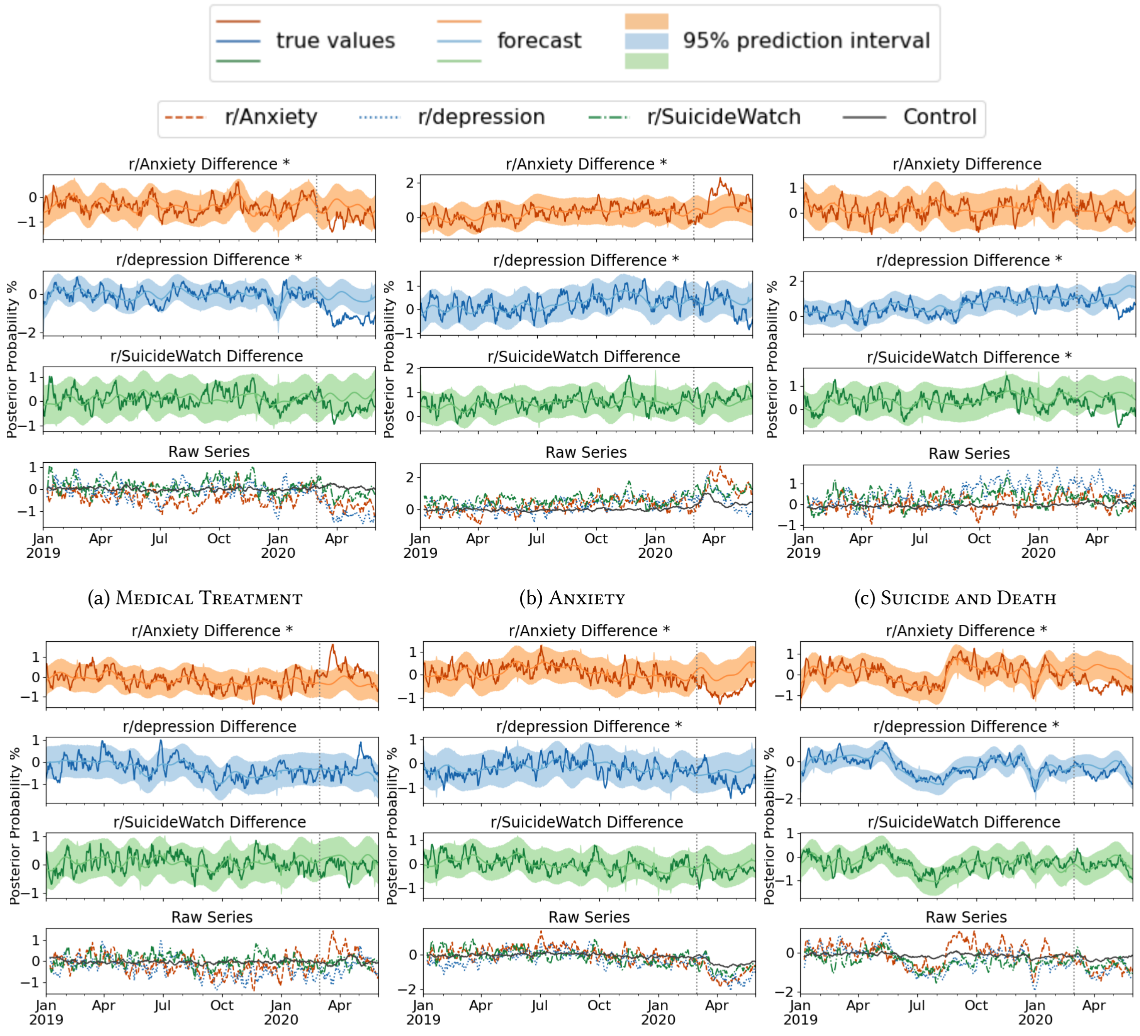
The significant increase in I in r/depression posts beyond what has occurred in control subreddits is somewhat concerning, given that usage of I has been shown to correlate with depression [50]. However, it may simply indicate an increase in discussion directly related to personal concerns. Meanwhile, discussion in r/Anxiety comments appears to be moving away from personal experiences, as is indicated by a decrease in personal pronouns (Figure 6e), despite the sharp increase in a single category (We). We suspect that this is linked to the large percentage of comments concerning the virus itself (Section 6.1), as well as the decrease in discussion of social relationships overall (Figure 6d) and decrease in Affect words (Figure 6c). These conversations appear to have taken a more informational tone, as is indicated by an increase in numerical information being shared (Figure 6f). The changes we have seen on r/Anxiety, particularly within comments, indicate that people with anxiety disorders may be more affected by the numerous economical, social, and health impacts of the pandemic (see increased discussion of Death in Table 5). It is important to consider the ongoing social support that they need.

6.4.2 Topic Analysis. We use our topic model, which was trained on posts collected from the mental health subreddits, to explore how discussion around common mental health related concerns has changed in both the mental health and control subreddits.

Results. We report the ten topics with the highest proportion of outliers in each of the mental health subreddits in Table 6. Within both r/Anxiety and r/depression, we find that there are significant changes in discussion related to Anxiety and its symptoms (keywords include: "panic," "heart," and "chest") compared to the control subreddits. Looking at the raw series plot in Figure 7b, we see that within the control posts, there is a spike in discussion of Anxiety throughout March and early April. Even with this increase, we still find that discussion rates of the Anxiety topic within the r/Anxiety posts are significantly higher than in the control subreddits during the COVID-19 period. We also observe a significant decrease in Anxiety discussion on r/depression for both posts (Figure 7b) and comments (Table 6).

Table 6. Ten topics with the highest proportion of outliers in each subreddit for posts and comments. Arrows mark the direction in which the mean of the outliers shifted from the predicted mean. Categories marked with * have a statistically significant percentage of outliers (with Bonferroni correction; $\alpha = 0.05$ before correction).

	r/Anxiety			r/depression			r/SuicideWatch		
	Topic	% Outliers		Topic	% Outliers		Topic	% Outliers	
Posts	Transport and Daily Life*	82	↓	Medical Treatment*	79	↓	Suicide and Death *	37	↓
	School*	54	↓	Sleep and Routine*	67	↓	Friends	16	↓
	Anxiety*	45	↑	Family and Children*	58	↑	Medical Treatment	13	↓
	Information Sharing*	35	↑	Feelings*	47	↓	Family and Home	11	↑
	Family and Home*	32	↑	Suicide and Death *	41	↓	Family and Children	11	↑
	"Game-over" Mentality and Swearing*	32	↓	Family and Home*	36	↑	Time	9	↓
	Medical Treatment*	29	↓	Communication*	34	↑	Information Sharing	8	↓
	Body and Food*	17	↑	"Game-over" Mentality and Swearing*	33	↑	School	7	↑
	Motivation*	17	↓	Motivation*	27	↓	Sleep and Routine	7	↓
	Life and Philosophy	15	↓	Transport and Daily Life*	26	↓	Worry	7	↓
Comments	Information Sharing*	99	↑	Transport and Daily Life*	67	↓	Time*	78	↓
	Family and Home*	85	↑	Sleep and Routine*	57	↓	"Game-over" Mentality and Swearing*	25	↑
	Experience and Mental State*	85	↑	Time*	52	↓	Family and Home*	22	↓
	Motivation*	82	↓	Information Sharing*	49	↑	Sleep and Routine*	22	↓
	Feelings*	82	↓	Medical Treatment*	47	↓	Relationships*	20	↑
	Worry*	68	↓	Body and Food*	39	↓	Motivation	18	↑
	Medical Treatment*	55	↓	Anxiety*	37	↓	Suicide and Death	16	↓
	Life and Philosophy*	53	↑	Motivation*	35	↑	Anxiety	16	↓
	Relationships*	50	↓	Experience and Mental State*	34	↑	People and Behavior	13	↑
	Friends*	48	↓	"Game-over" Mentality and Swearing*	28	↓	Friends	12	↓



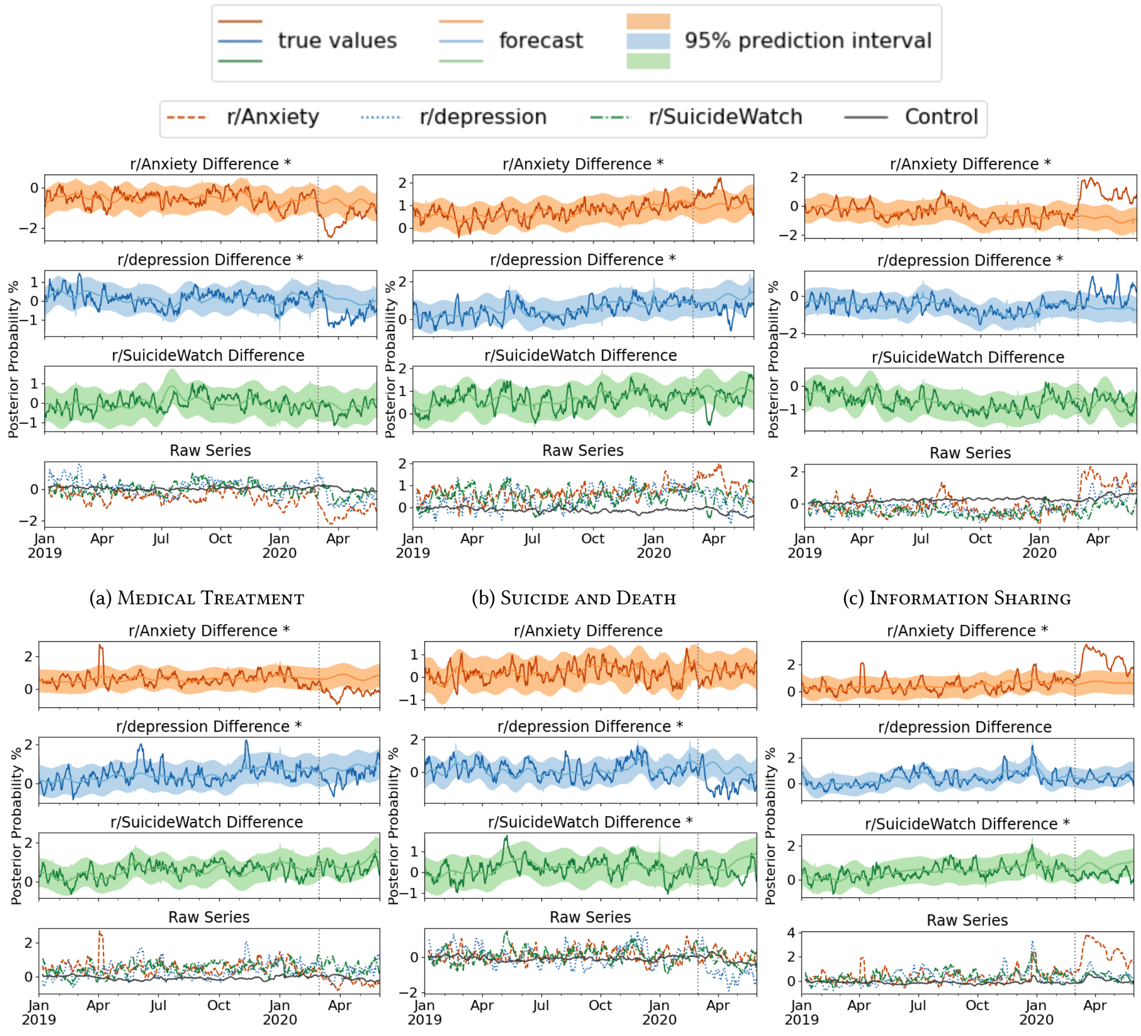
(a) Medical Treatment (b) Anxiety (c) Suicide and Death

(d) Information Sharing (e) Transport and Daily Life (f) School

Fig. 7. Average daily difference in topic posterior probability (normalized) across posts from a selection topics over time. The lighter line is the Prophet forecast, the shaded area is the 95% prediction interval, and the darker line is the true value. Subreddits marked with * have a statistically significant percentage of outliers (with Bonferroni correction; $\alpha = 0.05$ before correction).

We observe significant changes in rates of discussion of the Suicide and Death topic. On both r/depression and r/SuicideWatch, there is a decrease in Suicide and Death related discussions for both posts (Figure 7c) and comments (Figure 8b). In contrast, in r/Anxiety comments, we see a significant increase in the Suicide and Death topic compared to the control subreddits (Figure 8b).

Examining the Medical Treatment topic (keywords include: "medication," "doctor," and "therapy"), we see significant decreases in the r/Anxiety and r/depression subreddits with respect to the control subreddits for both posts (Figure 7a) and comments (Figure 8a). We also observe reductions in discussion of the School topic within r/Anxiety and r/depression



(a) Medical Treatment (b) Suicide and Death (c) Information Sharing

(d) Feelings (e) Sleep and Routine (f) Family and Home

Fig. 8. Average daily difference in topic posterior probability (normalized) across comments from a selection topics over time. The lighter line is the Prophet forecast, the shaded area is the 95% prediction interval, and the darker line is the true value. Subreddits marked with * have a statistically significant percentage of outliers (with Bonferroni correction; $\alpha = 0.05$ before correction).

posts (Figure 7f), and reductions in the Transport and Daily Life topic (keywords include: “drive,” “car,” “time”, and “day”) within r/Anxiety posts and r/depression posts (Figure 7e) and comments (Table 6). Finally, we see significant decreases in the rates of discussion of the Sleep and Routine topic (keywords include: “sleep,” “wake,” and “week") within r/depression posts (Table 6), as well as comments on both r/depression and r/SuicideWatch (Figure 8e).

While rates of discussion of certain common concerns decrease, we find the opposite trend for the Family and Home and the Information Sharing topics. Rates of discussion of Family and Home increase for posts on both r/Anxiety and r/depression (Table 6). We observe a particularly large spike in this topic within r/Anxiety comments (Figure 8f). For the Information Sharing topic (keywords include: "post," "read," "share," and "hope"), we see significant increases in r/Anxiety posts and comments (Figure 7d) as well as r/depression comments (Figure 8c) during the post-COVID period.

Discussion. The spike in discussion of Anxiety in March and early April in the control subreddits is not surprising given that anxiety is a commonly observed psychological response to pandemics within the general population [8]. The significantly higher discussion rates of Anxiety on r/Anxiety compared to the control subreddits suggests that anxiety-prone individuals are more likely to experience heightened anxiety during COVID-19. This observation reinforces warnings from the psychiatric literature that people with mental health disorders are especially vulnerable to the negative mental health effects of pandemics [59, 67]. Meanwhile, on r/depression, we see that a decrease in Anxiety discussion occurs towards the end of our analyzed post-COVID period. We hypothesize that this could be due to a reduction in social anxiety (which is frequently comorbid with depression [53]), as social distancing measures have reduced opportunities for social interaction. However, additional work is needed to validate whether or not this is indeed the case.

While the results showing a decrease in Suicide and Death related discussions on both r/depression and r/SuicideWatch appear encouraging, they should be interpreted with caution. These observations seem to contradict prior work that has found that deaths by suicide increased during certain previous pandemics [20] and that unemployment (which has increased as a result of COVID-19) is associated with elevated suicide risk [27]. Therefore, this trend may change in the future, especially as the longer term economic and social effects of the COVID-19 pandemic take hold. While the significant increase in the Suicide and Death topic in r/Anxiety comments seems somewhat alarming, this finding may be driven by an increase in discussions of death outside of the context of suicide; the Suicide and Death topic keywords include "die" and "death," and in our LIWC analysis, we see that mentions of the Death category increased significantly for r/Anxiety comments (Table 5). Pandemics can lead people to experience heightened anxiety around death and the possibility of loved ones dying [29, 44], which could be contributing to the increase in discussions involving mentions of "death."

The amount of discussion related to Medical Treatment on the control subreddits (see the "Raw Series" sub-plots in Figure 7a and Figure 8a) has remained relatively constant during COVID-19, indicating that the decreases in this topic seen on r/Anxiety and r/depression stem from a reduction in discussion of Medical Treatment on the mental health subreddits rather than an increase in discussion on the control subreddits. We found this result to be somewhat surprising; given that efforts to prevent the spread of COVID-19 have made it more difficult to access in-person healthcare, we thought that Medical Treatment might be a more frequently discussed concern. However, it also may be the case that since people have reduced access to therapy and treatment, they are discussing their experiences with these less frequently.

The observed decreases in discussion related to the Transport and Daily Life and Sleep and Routine topics aligned with our expectations and likely reflect the disruption to normal daily life caused by COVID-19. Quarantine practices have led to a large reduction in driving and other forms of transportation [14], and more generally, to a disruption in daily routines. To the extent that these results indicate an abandonment of routine, they are also somewhat concerning, as evidence from prior outbreaks suggests that getting back into normal routines helps to reduce loneliness and anxiety during quarantines [24].

While we expected there to be an increase in School-related discussions during the post COVID-19 period, we instead observe a significant reduction on both r/Anxiety and r/depression. Although the pandemic has led to a disruption in normal schooling practices, it may be that any increase in concern related to education is overshadowed by newly emerging concerns specifically related to COVID-19 (See Section 6.1). The increase in discussion of the Family and Home topic is consistent with both our hypotheses and with the increase in the Family category observed in our LIWC analysis (Section 6.4.1).

Information Sharing increased significantly in both posts and comments on r/Anxiety and within comments on r/depression, which aligns with our observation in the LIWC analysis section (6.4.1) that conversations on r/Anxiety have become less personal and more informative; we believe the rise in Information Sharing may similarly be tied to a desire to seek out and share information related to COVID-19. Further, individuals who experience health anxiety are more likely to exhibit online health information seeking behavior [36], which may help to explain the particularly large spike we observe in the Information Sharing topic within r/Anxiety comments. This result is potentially worrisome given the correlation between news consumption and anxiety that has been observed during COVID-19 [17]. However, the inclusion of words like "share," "hope," and "story" within the Information Sharing topic suggests that the increase in Information Sharing could also be indicative of a collective coping process, in which individuals come together for social support. This type of coping strategy has frequently been observed during past disease outbreaks [8] and may also be reflected by the increased usage of We we saw in r/Anxiety discussions (see Section 6.4.1).

7 APPLICATIONS

The methodology introduced in this paper, implemented in the system described in Figure 1, has a large range of applications. Below, we highlight both direct applications of our findings and additional areas in which our methodology could be applied.

7.1 Interventions and Allocation of Community Resources During COVID-19

The findings from this work could be useful to cross-disciplinary teams of forum moderators, systems designers, and public health officials. Moderators could monitor changes in their forum, and consider targeted interventions. If they note, for instance, that people are not getting medical treatment or are frequently discussing family, they can share resources that will be helpful to members of their community. After such an intervention, they could repeat the analysis with a new intervention date to measure the effect. Designers of systems such as chatbots for pandemic relief may also be interested in the findings from our work [31, 39, 63]. Knowing, for instance, that work is not a major source of concern among the populations that we study during the pandemic could allow them to focus their efforts on other issues, like giving information about access to medical treatment. While these forums and chatbots are also important to the general population, it is especially important that they consider those with mental health concerns during this time [59, 67].

The system allows for real-time tracking of need during the pandemic; we are able to see which communities are most affected, and which topics are preeminent in their discussions. By simply ranking metrics by percentage of outliers, we can see in which ways community behavior has deviated from the expected pattern following the stimulus (in this case, the start of the COVID-19 pandemic). Public health officials could use this information to provide pop-up support in their community that focuses on the issues that are prominent in discussions.

7.2 Exploring Upheaval Effects on Sub-communities

The community structure of Reddit presents an opportunity to understand the effect of a stimulus on communities. In our work, we study mental health communities and compare metrics in those communities to a broader population of Reddit users. However, there are many ways in which Reddit posting activity can be used to identify sub-populations along the lines of political activity (e.g., r/WayOfTheBern, r/Conservative), geographic position (e.g., r/berlin, r/vancouver), professions (e.g., r/medicine, r/ProgrammerHumor), and sexual orientation and gender identity (e.g., r/AskWomen, r/AskMen, r/lgbt, r/asktransgender), among others.

Using a method like ours involving time series analysis is likely necessary to study medium to long-term effects of events on different populations on Reddit, as the features that we extract tend to have trends and seasonal components. A natural application of our system would be studying the effects of the COVID-19 pandemic, or another pandemic or natural disaster on other sub-populations, such as healthcare professionals or the LGBT population. Another distinct application is studying what the lasting effects of an election are - insight into these effects could be useful for political campaign organizers.

While we use lexical features, topic modeling, and features of a user interaction network in our work, our architecture (Figure 1) is fairly general, and could be applied to any feature for which it is possible to extract a daily value. We break up our data into target and control data using subreddits, but it would also be possible to study different cross-sections of users, such as users who have posted in both mental health and COVID-19 discussion subreddits, or users who posted in mental health subreddits a year ago but are no longer active in those communities.

8 LIMITATIONS

With respect to the capabilities of our system, one limitation is that the numerical output (i.e., percentage of outliers) only indicates a specific type of change: sustained outliers that exceed a certain threshold. This is sufficient to answer our research questions to some extent, although careful studying of the graphs was necessary to gain a full understanding of whether a given percentage of outliers represented an immediate reaction to lockdown orders or a slowly emerging trend. In these cases, Prophet still gives us some guidance as to whether each day's datapoint is outside of the expected interval, which is useful in interpreting the time series graphs.

Additionally, our method primarily interprets the effect of a single intervention. It would need to be extended if we wanted to characterize changes during different parts of a one-year period or find various change points. Furthermore, as we only account for a single intervention and general trends in the data, external events might lead us to discover changes that are not related to the target event. For example, if we were to repeat this analysis using observations of Reddit posts created in Fall of 2020, the 2020 United States general election might lead to changes in posting patterns that are not related to COVID-19.

As a tool to study populations, our system also has some limitations: there may be multiple interpretations of the trends, and online communities may not perfectly match local communities (for instance, Reddit is largely male). However, even if the trends that we discover cannot always point directly to a solution, they can serve as indicators to officials that further investigation within their community is warranted.

9 CONCLUSIONS

In this study, we used an intervention analysis approach to determine how activity in mental health subreddits has changed in the face of the COVID-19 pandemic. We examine interaction metrics related to how users engage with the subreddits, in addition to metrics related to the content of posts and comments. While the scope of study is limited to mental health, the system we built is general and could be used in numerous domains to study the effect of a stimulus on any community.

We predominantly found a decrease in activity on mental health subreddits, with an increase in activity on the control subreddits, leading to a widening gap between the two. We saw some notable changes in discussion content across the subreddits centered around three general topics: stay home orders, physical health effects, and economic effects. Some changes were expected due to the nature of the pandemic and stay at home orders, such as decreases in the Transport and Daily Life topic and increases in Anxiety. However, we also saw some surprising shifts, such as a decrease in discussion of Work. Meanwhile, increases in topics like Information Sharing showed how the forums evolved to become a place in which people more frequently discuss and exchange information about current events, namely the pandemic.

There are numerous ways in which these findings can be applied with the goal of improving mental health: moderators can see the current needs of their users and share appropriate resources, developers building automated support systems can identify areas that are of the utmost concern and should be focal points, and local public health officials can use the trends to provide suitable pop-up support for their community. Knowing current trends and how they differ among people with a variety of mental health disorders would allow for more effective interventions.

REFERENCES

[1] Jason Baumgartner, Savvas Zannettou, Brian Keegan, Megan Squire, and Jeremy Blackburn. 2020. The Pushshift Reddit Dataset. *Proceedings of the International AAAI Conference on Web and Social Media* 14, 1 (May 2020), 830–839. https://aaai.org/ojs/index.php/ICWSM/article/view/7347

[2] Laura Biester, Katie Matton, Janarthanan Rajendran, Emily Mower Provost, and Rada Mihalcea. 2020. Quantifying the Effects of COVID-19 on Mental Health Support Forums. In *Proceedings of the 1st Workshop on NLP for COVID-19 (Part 2) at EMNLP 2020*. Association for Computational Linguistics, Online. https://doi.org/10.18653/v1/2020.nlpcovid19-2.8

[3] David M Blei, Andrew Y Ng, and Michael I Jordan. 2003. Latent dirichlet allocation. *Journal of machine Learning research* 3, Jan (2003), 993–1022. https://www.jmlr.org/papers/volume3/blei03a/blei03a.pdf

[4] George E. P. Box and Gwilym M. Jenkins. 1976. *Time series analysis: forecasting and control*. Holden-Day.

[5] Dante Chakravorti, Kathleen Law, Jonathan Gemmell, and Daniela Raicu. 2018. Detecting and Characterizing Trends in Online Mental Health Discussions. In *2018 IEEE International Conference on Data Mining Workshops (ICDMW)*. 697–706. https://doi.org/10.1109/ICDMW.2018.00107

[6] Stevie Chancellor and Munmun De Choudhury. 2020. Methods in predictive techniques for mental health status on social media: a critical review. *NPJ digital medicine* 3, 1 (2020), 1–11. https://doi.org/10.1038/s41746-020-0233-7

[7] Nicola Cherry. 1978. Stress, anxiety and work: A longitudinal study. *Journal of Occupational Psychology* 51, 3 (1978), 259–270. https://doi.org/10.1111/j.2044-8325.1978.tb00422.x

[8] Qian Hui Chew, Ker Chiah Wei, Shawn Vasoo, Hong Choon Chua, and Kang Sim. 2020. Narrative synthesis of psychological and coping responses towards emerging infectious disease outbreaks in the general population: practical considerations for the COVID-19 pandemic. *Singapore Medical Journal* April (apr 2020), 1–31. https://doi.org/10.11622/smedj.2020046

[9] Glen Coppersmith, Mark Dredze, and Craig Harman. 2014. Quantifying Mental Health Signals in Twitter. In *Proceedings of the Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality*. Association for Computational Linguistics, Baltimore, Maryland, USA, 51–60. https://doi.org/10.3115/v1/W14-3207

[10] Munmun De Choudhury and Sushovan De. 2014. Mental health discourse on Reddit: Self-disclosure, social support, and anonymity. In *Eighth international AAAI conference on weblogs and social media*. 71–80. https://www.aaai.org/ocs/index.php/ICWSM/ICWSM14/paper/viewFile/8075/8107

[11] Munmun De Choudhury, Michael Gamon, Scott Counts, and Eric Horvitz. 2013. Predicting depression via social media. In *Seventh international AAAI conference on weblogs and social media*. 128–139. https://www.aaai.org/ocs/index.php/ICWSM/ICWSM13/paper/viewFile/6124/6351

[12] Munmun De Choudhury, Emre Kiciman, Mark Dredze, Glen Coppersmith, and Mrinal Kumar. 2016. Discovering Shifts to Suicidal Ideation from Mental Health Content in Social Media. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI '16)*. Association for Computing Machinery, New York, NY, USA, 2098–2110. https://doi.org/10.1145/2858036.2858207

[13] Deborah J DeWolfe. 2000. *Training manual for mental health and human service workers in major disasters*. US Department of Health and Human Services, Substance Abuse and Mental Health Services Administration, Center for Mental Health Services. https://files.eric.ed.gov/fulltext/ED459383.pdf

[14] Camila Domonoske and Stephanie Adeline. 2020. The Pandemic Emptied American Roads. But Driving Is Picking Back Up. *NPR* (May 2020). https://web.archive.org/web/20200623073738/https://www.npr.org/sections/coronavirus-live-updates/2020/05/06/851001762/the-pandemic-emptied-american-roads-but-driving-is-picking-back-up

[15] Sindhu Kiranmai Ernala, Asra F. Rizvi, Michael L. Birnbaum, John M. Kane, and Munmun De Choudhury. 2017. Linguistic Markers Indicating Therapeutic Outcomes of Social Media Disclosures of Schizophrenia. *Proc. ACM Hum.-Comput. Interact.* 1, CSCW, Article 43 (Dec. 2017), 27 pages. https://doi.org/10.1145/3134678

[16] Johannes Feldhege, Markus Moessner, and Stephanie Bauer. 2020. Who says what? Content and participation characteristics in an online depression community. *Journal of Affective Disorders* 263 (2020), 521–527. https://doi.org/10.1016/j.jad.2019.11.007

[17] Miquel A Fullana, Diego Hidalgo-Mazzei, Eduard Vieta, and Joaquim Radua. 2020. Coping behaviors associated with decreased anxiety and depressive symptoms during the COVID-19 pandemic and lockdown. *Journal of Affective Disorders* 275 (2020), 80–81. https://doi.org/10.1016/j.jad.2020.06.027

[18] Oguzhan Gencoglu and Mathias Gruber. 2020. Causal Modeling of Twitter Activity during COVID-19. *Computation* 8, 4 (2020). https://doi.org/10.3390/computation8040085

[19] Neil Greenberg, Mary Docherty, Sam Gnanapragasam, and Simon Wessely. 2020. Managing mental health challenges faced by healthcare workers during covid-19 pandemic. *BMJ* 368 (2020). https://doi.org/10.1136/bmj.m1211

[20] David Gunnell, Louis Appleby, Ella Arensman, Keith Hawton, Ann John, Nav Kapur, Murad Khan, Rory C O'Connor, Jane Pirkis, Eric D Caine, et al. 2020. Suicide risk and prevention during the COVID-19 pandemic. *The Lancet Psychiatry* 7, 6 (2020), 468–471. https://doi.org/10.1016/S2215-0366(20)30171-1

[21] Aric A. Hagberg, Daniel A. Schult, and Pieter J. Swart. 2008. Exploring Network Structure, Dynamics, and Function using NetworkX. In *Proceedings of the 7th Python in Science Conference*, Gaël Varoquaux, Travis Vaught, and Jarrod Millman (Eds.). Pasadena, CA USA, 11 – 15. https://www.osti.gov/biblio/960616

[22] S. Hochreiter and J. Schmidhuber. 1997. Long Short-Term Memory. *Neural Computation* 9 (1997), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

[23] Xiaolei Huang, Amelia Jamison, David Broniatowski, Sandra Quinn, and Mark Dredze. 2020. *Coronavirus Twitter Data: A collection of COVID-19 tweets with automated annotations.* https://doi.org/10.5281/zenodo.3897727 http://twitterdata.covid19dataresources.org/index.

[24] Damir Huremović. 2019. *Psychiatry of Pandemics: A Mental Health Response to Infection Outbreak.* Springer International Publishing, Cham. https://link.springer.com/book/10.1007%2F978-3-030-15346-5

[25] Molly Ireland and Micah Iserman. 2018. Within and Between-Person Differences in Language Used Across Anxiety Support and Neutral Reddit Communities. In *Proceedings of the Fifth Workshop on Computational Linguistics and Clinical Psychology: From Keyboard to Clinic*. Association for Computational Linguistics, New Orleans, LA, 182–193. https://doi.org/10.18653/v1/W18-0620

[26] Gloria J Kang, Sinclair R Ewing-Nelson, Lauren Mackey, James T Schlitt, Achla Marathe, Kaja M Abbas, and Samarth Swarup. 2017. Semantic network analysis of vaccine sentiment in online social media. *Vaccine* 35, 29 (2017), 3621–3638. https://doi.org/10.1016/j.vaccine.2017.05.052

[27] Wolfram Kawohl and Carlos Nordt. 2020. COVID-19, unemployment, and suicide. *The Lancet Psychiatry* 7, 5 (2020), 389–390. https://doi.org/10.1016/S2215-0366(20)30141-3

[28] Ella Koeze and Nathaniel Popper. 2020. The Virus Changed the Way We Internet. https://www.nytimes.com/interactive/2020/04/07/technology/coronavirus-internet-use.html

[29] Anant Kumar and K Rajasekharan Nayar. 2020. COVID 19 and its mental health consequences. *Journal of Mental Health* (2020), 1–2. https://doi.org/10.1080/09638237.2020.1757052

[30] Mrinal Kumar, Mark Dredze, Glen Coppersmith, and Munmun De Choudhury. 2015. Detecting Changes in Suicide Content Manifested in Social Media Following Celebrity Suicides. In *Proceedings of the 26th ACM Conference on Hypertext & Social Media - HT '15*, Vol. 176. ACM Press, New York, New York, USA, 85–94. https://doi.org/10.1145/2700171.2791026

[31] Yunyao Li, Tyrone Grandison, Patricia Silveyra, Ali Douraghy, Xinyu Guan, Thomas Kieselbach, Chengkai Li, and Haiqi Zhang. 2020. Jennifer for COVID-19: An NLP-Powered Chatbot Built for the People and by the People to Combat Misinformation. In *Proceedings of the 1st Workshop on NLP for COVID-19 at ACL 2020*. Association for Computational Linguistics, Online. https://www.aclweb.org/anthology/2020.nlpcovid19-acl.9

[32] Yaoyiran Li, Rada Mihalcea, and Steven R Wilson. 2018. Text-based detection and understanding of changes in mental health. In *International Conference on Social Informatics*. Springer, 176–188. https://doi.org/10.1007/978-3-030-01159-8_17

[33] Daniel M Low, Laurie Rumker, Tanya Talkar, John Torous, Guillermo Cecchi, and Satrajit S Ghosh. 2020. Natural language processing reveals vulnerable mental health support groups and heightened health anxiety on Reddit during COVID-19: an observational study. https://doi.org/10.31234/osf.io/xvwcy

[34] Mayo Clinic. 2018. Depression (major depressive disorder) - Symptoms and causes. https://www.mayoclinic.org/diseases-conditions/depression/symptoms-causes/syc-20356007 Accessed: 2020-10-09.

[35] Andrew Kachites McCallum. 2002. MALLET: A Machine Learning for Language Toolkit. http://mallet.cs.umass.edu

[36] Ryan D McMullan, David Berle, Sandra Arnáez, and Vladan Starcevic. 2019. The relationships between health anxiety, online health information seeking, and cyberchondria: Systematic review and meta-analysis. *Journal of affective disorders* 245 (2019), 270–278. https://doi.org/10.1016/j.jad.2018.11.037

[37] Maria Melchior, Avshalom Caspi, Barry J Milne, Andrea Danese, Richie Poulton, and Terrie E Moffitt. 2007. Work stress precipitates depression and anxiety in young, working women and men. *Psychological medicine* 37, 8 (Aug 2007), 1119–1129. https://doi.org/10.1017/S0033291707000414

[38] David Mimno, Hanna Wallach, Edmund Talley, Miriam Leenders, and Andrew McCallum. 2011. Optimizing Semantic Coherence in Topic Models. In *Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, Edinburgh, Scotland, UK., 262–272. https://www.aclweb.org/anthology/D11-1024

[39] Adam S Miner, Liliana Laranjo, and A Baki Kocaballi. 2020. Chatbots in the fight against the COVID-19 pandemic. *npj Digital Medicine* 3, 1 (2020), 65. https://doi.org/10.1038/s41746-020-0280-0

[40] Margaret Mitchell, Kristy Hollingshead, and Glen Coppersmith. 2015. Quantifying the Language of Schizophrenia in Social Media. In *Proceedings of the 2nd Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality*. Association for Computational Linguistics, Denver, Colorado, 11–20. https://doi.org/10.3115/v1/W15-1202

[41] Arijit Nandi, Melissa Tracy, John R Beard, David Vlahov, and Sandro Galea. 2009. Patterns and predictors of trajectories of depression after an urban disaster. *Annals of epidemiology* 19, 11 (2009), 761–770. https://doi.org/10.1016/j.annepidem.2009.06.005

[42] M. E. J. Newman. 2003. Mixing patterns in networks. *Phys. Rev. E* 67 (Feb 2003), 026126. Issue 2. https://doi.org/10.1103/PhysRevE.67.026126

[43] Catherine Ordun, Sanjay Purushotham, and Edward Raff. 2020. Exploratory Analysis of Covid-19 Tweets using Topic Modeling, UMAP, and DiGraphs. arXiv:2005.03082 [cs.SI]

[44] Felipe Ornell, Jaqueline B Schuch, Anne O Sordi, and Felix Henrique Paim Kessler. 2020. "Pandemic fear" and COVID-19: mental health burden and strategies. *Brazilian Journal of Psychiatry* 42, 3 (2020), 232–235. https://doi.org/10.1590/1516-4446-2020-0008

[45] Umashanthi Pavalanathan and Munmun De Choudhury. 2015. Identity management and mental health discourse in social media. In *Proceedings of the 24th International Conference on World Wide Web*. 315–321. https://doi.org/10.1145/2740908.2743049

[46] James W Pennebaker, Ryan L Boyd, Kayla Jordan, and Kate Blackburn. 2015. *The development and psychometric properties of LIWC2015*. Technical Report. https://repositories.lib.utexas.edu/bitstream/handle/2152/31333/LIWC2015_LanguageManual.pdf

[47] James W Pennebaker and Kent D Harber. 1993. A Social Stage Model of Collective Coping: The Loma Prieta Earthquake and The Persian Gulf War. *Journal of Social Issues* 49, 4 (1993), 125–145. https://doi.org/10.1111/j.1540-4560.1993.tb01184.x

[48] Jianyin Qiu, Bin Shen, Min Zhao, Zhen Wang, Bin Xie, and Yifeng Xu. 2020. A nationwide survey of psychological distress among Chinese people in the COVID-19 epidemic: implications and policy recommendations. *General psychiatry* 33, 2 (2020). https://doi.org/10.1136/gpsych-2020-100213

[49] Deblina Roy, Sarvodaya Tripathy, Sujita Kumar Kar, Nivedita Sharma, Sudhir Kumar Verma, and Vikas Kaushal. 2020. Study of knowledge, attitude, anxiety & perceived mental healthcare need in Indian population during COVID-19 pandemic. *Asian Journal of Psychiatry* (2020), 102083. https://doi.org/10.1016/j.ajp.2020.102083

[50] Stephanie S. Rude, Eva Maria Gortner, and James W. Pennebaker. 2004. Language use of depressed and depression-vulnerable college students. *Cognition and Emotion* 18, 8 (2004), 1121–1133. https://doi.org/10.1080/02699930441000030

[51] Cuihua Shen, Anfan Chen, Chen Luo, Jingwen Zhang, Bo Feng, and Wang Liao. 2020. Using Reports of Symptoms and Diagnoses on Social Media to Predict COVID-19 Case Counts in Mainland China: Observational Infoveillance Study. *Journal of Medical Internet Research* 22, 5 (May 2020), e19421. https://doi.org/10.2196/19421

[52] Judy Hanwen Shen and Frank Rudzicz. 2017. Detecting Anxiety through Reddit. In *Proceedings of the Fourth Workshop on Computational Linguistics and Clinical Psychology — From Linguistic Signal to Clinical Reality*. Association for Computational Linguistics, Vancouver, BC, 58–65. https://doi.org/10.18653/v1/W17-3107

[53] Murray B Stein, Martina Fuetsch, Nina Müller, Michael Höfler, Roselind Lieb, and Hans-Ulrich Wittchen. 2001. Social anxiety disorder and the risk of depression: a prospective community study of adolescents and young adults. *Archives of general psychiatry* 58, 3 (2001), 251–256. https://doi.org/10.1001/archpsyc.58.3.251

[54] Andreas Ströhle. 2009. Physical activity, exercise, depression and anxiety disorders. *Journal of neural transmission* 116, 6 (2009), 777–784. https://doi.org/10.1007/s00702-008-0092-x

[55] Acar Tamersoy, Munmun De Choudhury, and Duen Horng Chau. 2015. Characterizing smoking and drinking abstinence from social media. In *Proceedings of the 26th ACM Conference on Hypertext & Social Media*. 139–148. https://doi.org/10.1145/2700171.2791247

[56] Lei Tang and Huan Liu. 2010. Graph mining applications to social network analysis. In *Managing and Mining Graph Data*. Springer, 487–513. https://doi.org/10.1007/978-1-4419-6045-0_16

[57] Sean J. Taylor and Benjamin Letham. 2018. Forecasting at Scale. *The American Statistician* 72, 1 (jan 2018), 37–45. https://doi.org/10.1080/00031305.2017.1380080

[58] Julio Torales, Marcelo O'Higgins, João Mauricio Castaldelli-Maia, and Antonio Ventriglio. 2020. The outbreak of COVID-19 coronavirus and its impact on global mental health. *International Journal of Social Psychiatry* 66, 4 (2020), 317–320. https://doi.org/10.1177/0020764020915212

[59] Kim Usher, Navjot Bhullar, and Debra Jackson. 2020. Life in the pandemic: Social isolation and mental health. *Journal of Clinical Nursing* 29, 15-16 (2020), 2756–2757. https://doi.org/10.1111/jocn.15290

[60] Cuiyan Wang, Riyu Pan, Xiaoyang Wan, Yilin Tan, Linkang Xu, Cyrus S Ho, and Roger C Ho. 2020. Immediate psychological responses and associated factors during the initial stage of the 2019 coronavirus disease (COVID-19) epidemic among the general population in China. *International journal of environmental research and public health* 17, 5 (2020), 1729. https://doi.org/10.3390/ijerph17051729

[61] Tao Wang, Markus Brede, Antonella Ianni, and Emmanouil Mentzakis. 2017. Detecting and characterizing eating-disorder communities on social media. In *Proceedings of the Tenth ACM International conference on web search and data mining*. 91–100. https://doi.org/10.1145/3018661.3018706

[62] Duncan J Watts and Steven H Strogatz. 1998. Collective dynamics of 'small-world' networks. *nature* 393, 6684 (1998), 440–442. https://doi.org/10.1038/30918

[63] Charles Welch, Allison Lahnala, Veronica Perez-Rosas, Siqi Shen, Sarah Seraj, Larry An, Kenneth Resnicow, James Pennebaker, and Rada Mihalcea. 2020. Expressive Interviewing: A Conversational System for Coping with COVID-19. In *Proceedings of the 1st Workshop on NLP for COVID-19 (Part 2) at EMNLP 2020*. Association for Computational Linguistics, Online. https://doi.org/10.18653/v1/2020.nlpcovid19-2.6

[64] Hywel TP Williams, James R McMurray, Tim Kurz, and F Hugo Lambert. 2015. Network analysis reveals open forums and echo chambers in social media discussions of climate change. *Global environmental change* 32 (2015), 126–138. https://doi.org/10.1016/J.GLOENVCHA.2015.03.006

[65] Christo Wilson, Bryce Boe, Alessandra Sala, Krishna PN Puttaswamy, and Ben Y Zhao. 2009. User interactions in social networks and their implications. In *Proceedings of the 4th ACM European conference on Computer systems*. 205–218. https://doi.org/10.1145/1519065.1519089

[66] JT Wolohan. 2020. Estimating the effect of COVID-19 on mental health: Linguistic indicators of depression during a global pandemic. In *Proceedings of the 1st Workshop on NLP for COVID-19 at ACL 2020*. Association for Computational Linguistics, Online. https://www.aclweb.org/anthology/2020.nlpcovid19-acl.12

[67] Hao Yao, Jian-Hua Chen, and Yi-Feng Xu. 2020. Patients with mental health disorders in the COVID-19 epidemic. *The Lancet Psychiatry* 7, 4 (2020), e21. https://doi.org/10.1016/S2215-0366(20)30090-0

[68] Yingfei Zhang and Zheng Feei Ma. 2020. Impact of the COVID-19 pandemic on mental health and quality of life among local residents in Liaoning Province, China: A cross-sectional study. *International journal of environmental research and public health* 17, 7 (2020), 2381. https://doi.org/10.3390/ijerph17072381

[69] Francis W Zwiers and Hans Von Storch. 1995. Taking serial correlation into account in tests of the mean. *Journal of Climate* 8, 2 (1995), 336–351. https://doi.org/10.1175/1520-0442(1995)008<0336:TSCIAI>2.0.CO;2

[70] Ayşegül Şahin, Murat Tasci, and Jin Yan. 2020. The Unemployment Cost of COVID-19: How High and How Long? *Economic Commentary (Federal Reserve Bank of Cleveland)* (may 2020), 1–7. https://doi.org/10.26509/frbc-ec-202009

A EXCLUSION OF REMOVED DATA AND AUTOMODERATOR DATA

We exclude posts and comments from text-based analysis where the author or text is marked as '[removed]' or '[deleted]'. In our post count and user interaction analysis, we include posts and comments with deleted text and users when possible, because we found that data from the Pushshift (both the files and API) is not consistently scraped from Reddit at the same time with respect to when it was posted; this could cause us to see changes in the metrics that are not reflective of user activity. There are metrics in which it is impossible to consider deleted content (e.g., adding users with no username to the user graph, word count for deleted comments), and in those cases we exclude deleted data.

Additionally, we remove comments made by AutoModerator, a tool that enables Reddit moderators to create automatic replies, as in at least one subreddit it has been programmed to make COVID-19 specific responses.

B CONTROL SUBREDDITS

Table 7 shows a full list of our control subreddits.

Table 7. The control subreddits used in our analysis

Control Subreddits				
advice	asktransgender	edh	keto	relationship_advice
androidapps	buildapc	entrepreneur	learnprogramming	showerthoughts
androidquestions	buildapcforme	excel	learnpython	skyrimmods
applyingtocollege	casualconversation	fallout	legaladvice	suggestalaptop
askdocs	copypasta	findareddit	loseit	suggestmeabook
askgaybros	crazyideas	gamingsuggestions	mechmarket	sysadmin
askhistorians	cscareerquestions	guitar	nostupidquestions	techsupport
askmen	dating_advice	hardwareswap	offmychest	tipofmytongue
askouija	dndnext	homeimprovement	personalfinance	writing
asksciencefiction	dogs	jokes	r4r	writingprompts

C TOPICS IDENTIFIED BY LDA MODEL

Table 8. Topics identified by the LDA topic model. For each topic, we provide a summary label and the ten most probable words. We omit labels for topics whose keywords did not have a clear interpretation.

Topic Label	High Probability Words
School	school, year, college, high, class, fail, parent, study, grade, start
Relationships	love, relationship, girl, guy, good, girlfriend, break, date, meet, find
Experience and Mental State	experience, situation, mind, part, brain, lead, state, feeling, sense, learn
Communication	talk, call, time, phone, send, text, give, back, speak, message
People and Behavior	people, make, person, care, thing, understand, problem, wrong, act, attention
Feelings	happy, tired, cry, anymore, sad, make, hurt, depressed, stop, feeling
"Game-over" Mentality and Swearing	hate, fuck, shit, fucking, die, wanna, stupid, kill, literally, idk
Transport and Daily Life	drive, time, back, car, drink, start, walk, home, run, day
Time	year, month, start, time, back, ago, day, week, past, couple
Worry	thought, mind, fear, worry, head, afraid, scared, scare, stop, happen
Friends	friend, talk, people, good, social, play, make, close, hang, group
Anxiety	anxiety, attack, panic, anxious, heart, symptom, calm, chest, experience, stress
Medical Treatment	anxiety, medication, doctor, therapy, med, therapist, experience, week, mg, work
Body and Food	eat, body, eye, face, hand, head, sit, food, weight, walk
-	bad, thing, make, time, lot, happen, pretty, good, stuff, kind
Life and Philosophy	life, world, hope, exist, dream, human, live, pain, love, real
Depression and Mental Illness	depression, mental, issue, health, problem, struggle, deal, bad, suffer, year
Life Purpose	life, live, end, anymore, point, family, reason, care, worth, future
Motivation	thing, time, make, good, find, hard, work, enjoy, change, motivation
Work	work, job, money, pay, quit, find, afford, interview, company, month
Family and Children	year, family, mother, kid, parent, child, life, father, young, age
Information Sharing	post, read, write, find, hope, give, share, story, reddit, long
Family and Home	leave, mom, home, move, house, dad, family, live, parent, stay
Sleep and Routine	day, sleep, night, hour, wake, today, bed, morning, work, week
Suicide and Death	kill, die, suicide, pain, suicidal, end, attempt, cut, plan, dead

D SIGNIFICANCE TEST

We apply a one-sample proportion test to assess whether the percentage of observations outside of the prediction interval in the post-COVID period is significantly greater than 5%. This test assumes that the observations are independent; however, we find that there is order-1 autocorrelation in our data. We therefore apply a correction for order-1 autocorrelation [69] when computing the z-test statistic. The corrected test statistic is:

$$z = \frac{\hat{p} - p_0}{\sqrt{p_0(1 - p_0)(1 + r)/(n(1 - r))}} \tag{3}$$

where $\hat{p}$ is the proportion of observations outside of the prediction interval in the post-COVID period, $p_0 = .05$, n is the number of observations in the post-COVID period, and r is the lag-1 correlation coefficient of the pre-COVID data.

We use a Bonferroni correction when determining statistical significance for our discussion metrics (LIWC and topics), as we ran almost 600 tests ($M = 588$, which is the number of LIWC categories and topics multiplied by the number of subreddits and types of content (posts, comments)). Our corrected $\alpha = 0.05/588 = 8.5 \times 10^{-5}$. We also use a Bonferroni correction for interaction metrics (post count, user graph structure) ($M = 39$, which is the number of features multiplied by the number of subreddits). Out corrected $\alpha = 0.05/39 = 1.2 \times 10^{-3}$.