Mental Health and Behavior of College Students in the COVID-19 Pandemic : A Longitudinal Mobile Smartphone and Ecological Momentary Assessment Study- Part II

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Abstract

Background

Since late 2019, the lives of people across the globe have been disrupted by COVID-19. Millions of people have become infected; billions have been continually asked or required by local and national governments to change their behavioral patterns. Previous research on the COVID-19 pandemic suggests that it is associated with large-scale behavioral and mental health changes, but few studies have been able to track these changes with frequent, near real-time sampling or compare these changes to previous years of data for the same individuals.

Objectives

By combining mobile phone sensing and self-reported mental health data in a cohort of college-aged students enrolled in a longitudinal study, we seek to understand the behavioral and mental health impacts associated with the pandemic, measured by search term interest in “coronavirus” and “covid fatigue” across the United States.

Methods

Behaviors such as the number of locations visited, distance traveled, duration of phone usage, number of phone unlocks, sleep duration, and sedentary time were measured using the StudentLife mobile smartphone sensing app. Depression and anxiety were assessed using weekly self-reported Ecological Momentary Assessments (EMAs), including the Patient Health Questionnaire-4 (PHQ-4). Participants were 217 undergraduate students. Differences in behaviors and self-reported mental health collected during the Spring 2020 term, as compared to previous terms in the same cohort, were modeled using mixed linear models.

Results

Linear mixed models observed differences in phone usage, sleep, sedentary time and the number of locations visited associated with the COVID-19 pandemic. In further models, these behaviors were strongly associated with increased interest in covid fatigue. When mental health metrics (e.g., depression and anxiety) were added to the previous measures (week of term, number of locations visited, phone usage, sedentary time), both anxiety and depression ($P < .001$) were significantly associated with interest in covid fatigue. Notably, these behavioral and mental health changes are consistent with those observed around the initial implementation of COVID-19 lockdowns in the spring of 2020 [1].

Conclusions

In the initial lockdown phase of the COVID-19 pandemic, people spent more time on their phones, were more sedentary, visited fewer locations, and exhibited increased symptoms of anxiety and depression. As the pandemic persisted through the spring, people continued

to exhibit very similar changes in both mental health and behaviors. Though unsurprising, understanding these large-scale shifts in mental health and behaviors is critical in disrupting the negative consequences to mental health during the ongoing pandemic.

Introduction

The Coronavirus Pandemic

COVID-19 has drastically changed life for people worldwide. The World Health Organization (WHO) declared COVID-19 a pandemic on March 11, 2020 [2]. In the current work, we extend our previous research beyond the initial phases of the pandemic to June 25, 2020. By this time, the world had seen over 2,000,000 confirmed COVID-19 cases and 100,000 deaths [3], and the severe long-term political, economic, educational, and social ramifications of COVID-19 had grown increasingly acute. Understanding the behavioral and mental health implications for individuals during the spring of 2020, an unprecedented period of high stress, is critical for the upkeep of mental health during the pandemic.

College students seem to be vulnerable to the impacts of COVID-19 on mental health [4–6]. In the spring of 2020, global health measures forced many colleges to shut down in an effort to mitigate the spread of the virus. On March 12, 2020, Dartmouth College requested that students leave the campus, with hope that the campus could resume normal operations in 5 weeks. At that time, it was believed that COVID-19 would end rather quickly, but, by March 17, the severity of the virus became more apparent, and Dartmouth College announced that all classes and office hours would be held remotely during the Spring academic term. Students were asked to leave campus and not return until further notice. Following changes in both school, local, and federal policies, drastic alterations in students' behavior were observed. Prior research found that during the initial stages of the pandemic, this cohort of students visited fewer locations, spent more time sedentary, and increased its phone usage [1]. All of these behavioral changes were linked with increased levels of anxiety and depression [1], a trend seen by other researchers among various groups of college students [7,8]. Despite the negative impact on their mental health, many students continued to practice physical distancing with the hopes of a swift return to normalcy. Unfortunately, improved knowledge about the ways in which COVID-19 spreads made it increasingly clear that physical distancing and other measures needed to continue for the sake of public health. Though some localities began to ease their restrictions and reopen in April 2020, it was still widely suggested that people avoid public gatherings and maintain physical distance from others.

COVID-19 Restrictions Over the Long Haul

Figure 1. Number of confirmed COVID-19 cases graphed alongside search term interest (scaled from 0-100) during the winter and spring of 2020. COVID-19 case data was taken from the COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University. Search term interest was taken from Google Trends.

Towns and cities across the United States were forced to sustain COVID-19 “Stay Home, Stay Safe” restrictions in an effort to stem the spread of COVID-19. The effort of adhering to these restrictions seems to have bred fatigue among people nationwide. While there is evidence that these stay-at-home-orders resulted in an immediate suppression of negative changes in mental health brought on during this time [9], people grew weary of the effort required to maintain constant vigilance. For many, staying at home began to feel like a monotonous rut—many refer to this feeling as “COVID fatigue”. Search term interest in “COVID fatigue” is seen alongside interest in “coronavirus”, and the total number of confirmed COVID-19 cases [3] (Figure 1). Interest in COVID fatigue began to grow about a month into the pandemic (spiking in April) and continued to grow throughout the spring, while interest in “coronavirus” peaked around policy changes in March, before sharply and steadily declining. Therefore, COVID fatigue becomes an appropriate metric for measuring pandemic intensity at a given moment in time, while interest in the search term “coronavirus” seems to capture the initial pandemic-related changes, reaching peak interest levels in late March. Since many students continued to live under “Stay Home, Stay

Safe” restrictions throughout the spring, it is necessary to understand how the sustenance of these behaviors is related to mental health.

Over the last year, COVID-19 has prompted multiple lockdowns, which have brought about increased interest in the search term “COVID fatigue”, a term that has quickly become the subject of much discussion in public health research [10–13]. Cross-sectional research in Istanbul, Turkey suggests that those with higher-education levels experience more COVID-19 based fatigue [14], which may be attributable to this population being more likely to adhere to virus protocols and practice physical distancing [14,15]. Recent work proposes that college students may experience increases in depression due to COVID fatigue [16]. Most work measuring COVID fatigue has been limited to the use of online surveys, limiting these studies as they are unable to utilize objectively measured behavioral data to further investigate COVID-19 fatigue. Left to be answered are the questions of what behavioral and mental health changes are related to COVID fatigue among populations at high risk for mental health issues (e.g. college students).

Modeling Stages of the Pandemic with Changes in Behavior and Mental Health

Using previously successful methods, the current work seeks to infer the behavioral and mental health impacts of the pandemic’s initial onset and duration among a cohort of Dartmouth undergraduate students. Search-query related data is a promising metric in gathering population-based interest, which can be used to identify changes in mental health [9,17,18]. Prior work has shown EMAs to be an excellent tool for gathering real-time assessments of mental health [19]. Notably, researchers have also used EMAs to assess mental health changes during the COVID-19 pandemic [1,20]. Interest in the search terms ‘coronavirus’ and ‘covid fatigue’ was gathered from Google Trends to quantify the initial and ongoing phases of the pandemic (Figure 1). Interest levels were linearly inferred based on smartphone behavioral sensing data (gathered via passive sensing) and reported levels of anxiety and depression. Linear models are a useful tool in understanding COVID-19’s impact on daily behaviors and mental health in previous work, as a near identical method using COVID-19 media presence was previously successful[1]. The current work seeks to build on prior work conducted by this and other groups to gain further insight into the ways in which COVID-19 has impacted daily life and mental health.

Objective

The current work seeks to understand what behaviors and mental health changes are associated with the continuing phases of the pandemic, as inferred by search term interest in “covid fatigue” and “coronavirus”.

Methods

Study Design

All data from the current study comes from the second iteration of the StudentLife study [21], which is a longitudinal multimodal study, designed to follow the experiences of undergraduate students throughout their academic tenure with a focus on mental health. Study components include smartphone mobile sensing through the StudentLife app [22], ecological momentary assessments (EMAs), and surveys focusing on a variety of college experience components and functional neuroimaging [23].

Participants

Data was collected from 219 participants who agreed to provide mobile sensing data via the StudentLife app [22]. One subject was removed from the study for having a phone incompatible with the app, and one subject withdrew within a week of starting the study. Data for both subjects are excluded from further analyses. Of the remaining 217 participants, 67.8% (147) were female, with an age range of 18-22 years old at time of enrollment. Recruitment for this study began in August 2017 and concluded in November 2018. This study was reviewed and approved by Dartmouth's Committee for the Protection of Human Subjects. All data analyzed was collected from September 9, 2017 through June 25, 2020.

Academic Terms

At Dartmouth College, the academic schedule consists of a flexible, year-round calendar roughly divided into four ten-week academic terms (quarters), typically followed by two or more weeks of break. COVID-19 was first discovered in the United States during Dartmouth's Winter 2020 term, which began January 6, 2020. The Spring 2020 academic term (March 30 start date) was the first complete academic term occurring during the COVID-19 pandemic. To graphically show differences in anxiety and depression related to COVID-19, academic terms, including the subsequent two weeks of break prior to the Winter 2020 term, were included as control terms.

Mobile Sensing and Ecological Momentary Assessments

Smartphone sensing data and EMA surveys were administered using the StudentLife application (iOS & Android) [22]. The StudentLife app collects data from several of the phone's sensors, including, but not limited to, GPS, accelerometer, and lock/unlock status. Anonymized data from the StudentLife app is uploaded to a secure server whenever a participant is both connected to WiFi and charging their phone. Data from these sensors are used to assess, for example, the day-to-day and week-by-week impact of workload on stress, sleep, activity, mood, sociability, mental well-being, and academic performance [22]. Students are prompted weekly by the StudentLife application to complete a few short surveys, administered as Ecological Momentary Assessments (EMAs) [19]. These EMAs include the PHQ-4, which combines a brief measure of depressive and anxious symptoms

[24] that assesses how often individuals were bothered by specific symptoms over the last two weeks with values ranging from 0-6 for each subscale. The PHQ-4 combines the Patient Health Questionnaire-2 (PHQ-2) and the Generalized Anxiety Disorder-2 (GAD-2).

Sedentary Time

Sedentary time, or stationary duration, is computed with algorithms that detect a lack of movement based on accelerometer data from the phones' sensors. This allows us to measure students' activity or, more precisely, lack of activity level. The StudentLife app continuously infers physical activities using the Android activity recognition API [25,26] or iOS Core Motion [27].

Sleep

Sleep was inferred through a combination of passive sensing features (ambient light, movement activity, screen on/off). In this way, three features were computed: sleep onset, wake time, and sleep duration. These measures of sleep have been shown to be accurate within ± 30 minutes of total sleep duration [22].

Location

Density-based spatial clustering of applications with noise (DBSCAN) [28] was used to cluster GPS coordinates to determine the number of locations visited and distance traveled during a given time-period. Locations were detected when 3 GPS samples (sampled every 10 minutes) were within a radius of 30 meters. Distance was calculated in meters traveled between all locations throughout the day.

Phone Usage

Unlock duration is a measurement of time during which the phone is unlocked and the screen is on, calculated as the time between the user unlocking the phone and the user either manually relocking the phone or autolocking due to disuse (iOS default of 30 seconds, Android defaults vary by manufacturer, and users can alter this through their phones settings). Notification and system services do not influence the measurement of unlock duration. For the iOS app (189 users) from the start of the study in September 2017 until September 2018, unlock duration was measured by remotely triggering phones every 10 min, sampling 1 min every 10 min period (minimum 10% temporal coverage). After September 2018, phones were remotely triggered every 3 minutes with subsequent sampling for 1 minute. Lock/unlock behaviors within that minute are recorded in real time, while lock/unlocks for the remaining 2 minutes are logged during the next remote trigger. The Android phone app natively supports phone usage tracking and does not need to be triggered (28 users).

Google Trends

Google is the world's leading search engine, and Google Trends is an excellent tool to quantify topic interest. In turn, interest data from Google Trends has successfully been used to quantify changes in mental health [9,17,18]. Google data is posted publicly, and data can

be downloaded directly through Google's web portals or through freely available software. Google normalizes search data by region (in this case, the United States). To normalize the data, each data point is divided by the total searches of the geography and time range it represents to compare relative popularity; results are then scaled on a range of 0 to 100 based on a topic's proportion to all searches on all topics [29]. Search terms with a low interest appear as "0", while "100" reflects peak interest during a given period. To obtain an unbiased measurement of interest in "coronavirus" and "covid fatigue", interest in both search terms was pulled for the duration of the entire study (September 7, 2017 to June 25, 2020). Data received from Google Trends was reported on a weekly scale; interest was reported for each Sunday. To gather a more finely-grained real-time view of interest, the data was linearly interpolated using the 'approxm' function from the Freqprof package in Rstudio.

Data Processing, Modeling and Visualization in RStudio

Modeling was implemented in lme4 [30] and lmerTest [31]. All plots were generated using ggplot2 [32]. Result tables were produced using stargazer [33]. The following behaviors, inferred through mobile sensing, were standardized and plotted over the time course of January to July of 2020: locations visited, phone usage, sleep, and time still (Figure 2). The objective of the analyses was to determine how the shock and sustained nature of the pandemic have impacted behaviors and mental health. Term week was modeled as linear and quadratic factors. To get a variable mirroring interest in coronavirus and covid fatigue, topic interest in both coronavirus and covid fatigue was gathered from Google Trends. Interest levels were modeled with fixed effects of reported depression and anxiety levels, unlock duration, unlock number, sedentary time, sleep duration, number of locations visited, term week (linear and quadratic) variables, as well as random intercepts for each subject. Each variable except subject was scaled to aid model convergence. P-values were calculated using Satterthwaite's method as implemented in lmerModLmerTest as part of lmerTest.

Results

Behavioral and Mental Health Changes Associated with the COVID-19 Pandemic

Figure 2. Standardized daily scores of the number of locations visited, duration of time phone unlocked, sleep duration, and sedentary time before and after the WHO declared COVID-19 a global health pandemic (3/11/20). All behaviors were calculated using data from the StudentLife app.

Figure 3. Depression (top), and anxiety (bottom) scores across an academic term and the first 2 weeks of break, with the term influenced by the outbreak of the COVID-19 pandemic as a separate line. The shaded ribbons represent the standard error for each week. Winter 2020 weeks influenced by policy changes related to COVID-19 are represented with a shaded box from weeks 9 to 12. Colored text corresponds to the term in which the event took place. Depression and anxiety were measured with the PHQ-2 and GAD-2 scales through the StudentLife app. Control terms include data from the same group of individuals across previous academic terms. COVID-19: coronavirus disease; Finals: final examinations; GAD-2: Generalized Anxiety Disorder-2; PHQ-2: Patient Health Questionnaire-2.

To visually observe shifts in behaviors due to COVID-19, standardized scores were produced for each behavior plotted with a vertical line marking the WHO's calling COVID-19 a pandemic (Figure 2). Students visited fewer locations, used their phones more, spent more time sedentary, and initially exhibited increases in sleep before a sustained decrease in sleep. The mean values of depression and anxiety were plotted by week of the term; data were combined from all study participants from all terms prior to the Winter 2020 term, which was plotted as a separate line along with the Spring 2020 term. Standard error was plotted as a shaded ribbon surrounding the mean. Sustained increased levels of depression and anxiety throughout the Spring 2020 academic term compared to Winter 2020 and control terms were plotted (Figure 3). Peak self-reported anxiety and depression symptoms were observed during the 9th week of the Spring term, corresponding to the time before finals, increases in COVID-19 cases, and the murder of George Floyd. Linear models were produced to better assess these differences in a more quantitative manner.

Multiple models for sedentary time, phone usage, sleep, locations visited, depression, and anxiety were tested (see Methods for specifics). For all mobile sensing variables except phone usage, superior fit was observed with the most complex model that included the COVID-19 term, linear and quadratic term week trends, the interaction of COVID-19 term with each of the term week trends, and allowing for random intercepts for each participant's data (random effects). For phone usage, superior fit (measured by lowest deviance) was observed with the model including the COVID-19 term, linear and quadratic term week trends, and the interaction between the linear term week variable and the COVID-19 term. Modeling of the COVID-19 academic term compared with non-COVID-19 academic terms identified significantly increased sedentary time, phone usage, sleep, depression, and anxiety, along with a decrease in locations visited ($P < .001$; Table 1). Significant interactions of the COVID-19 term and quadratic term week regressor for sedentary time, locations visited, and anxiety ($P < .001$), as well as sleep and depression ($P = .05$) were observed. Significant interactions between the COVID-19 term and the linear term week regressor for locations visited, phone usage, and anxiety ($P < .001$) as well as sedentary time ($P = .01$) and depression ($P = .05$) were also observed.

Table 1. Models of sedentary time, depression, anxiety, locations visited, and sleep by week and presence of COVID-19 during the academic term.

	<i>Dependent variable:</i>					
	Sedentary Time	Locations Visited	Sleep Duration	Phone Usage	Depression	Anxiety
	(1)	(2)	(3)	(4)	(5)	(6)
COVID Term	0.469 (0.007) p = 0.000***	-0.851 (0.008) p = 0.000***	0.061 (0.008) p = 0.000***	0.406 (0.007) p = 0.000***	0.262 (0.013) p = 0.000***	0.150 (0.013) p = 0.000***
Term Week (Linear)	-0.056 (0.003) p = 0.000***	-0.218 (0.003) p = 0.000***	0.041 (0.003) p = 0.000***	0.072 (0.003) p = 0.000***	-0.014 (0.006) p = 0.015*	-0.042 (0.006) p = 0.000***
Term Week (Quadratic)	-0.036 (0.003) p = 0.000***	-0.140 (0.003) p = 0.000***	0.060 (0.003) p = 0.000***	0.013 (0.003) p = 0.000***	-0.074 (0.006) p = 0.000***	-0.108 (0.006) p = 0.000***
COVID Term : Term Week (Linear)	-0.021 (0.007) p = 0.003**	0.121 (0.008) p = 0.000***	-0.005 (0.007) p = 0.498	-0.032 (0.006) p = 0.000***	0.033 (0.013) p = 0.011*	0.086 (0.013) p = 0.000***
COVID Term : Term Week (Quadratic)	0.025 (0.007) p = 0.001***	0.071 (0.008) p = 0.000***	-0.017 (0.007) p = 0.023*		0.029 (0.013) p = 0.024*	0.088 (0.013) p = 0.000***
Constant	-0.099 (0.033) p = 0.003**	0.148 (0.025) p = 0.000***	0.010 (0.032) p = 0.749	-0.102 (0.043) p = 0.019*	-0.011 (0.046) p = 0.815	0.031 (0.045) p = 0.488
Observations	91541	85148	91541	91541	21284	21284

Note: p<0.05; p<0.01; p<0.001

Table 1. Models of sedentary time, locations visited, sleep duration, phone usage, depression, and anxiety by week and by presence of COVID-19 during the academic term.

COVID-19 Interest, Mental Health and Mobile Sensing

After observing broad differences in sleep, phone usage, locations visited, sedentary time, depression, and anxiety between the Winter 2020 term and previous terms, the next goal was to see if these behaviors changed on a daily scale, and particularly mirroring the relative interests in coronavirus and COVID fatigue over the study's duration. Interest in both variables was at zero until March of 2020 (Figure 1). To gather what and how behaviors changed with coronavirus interests we included fixed effects for phone usage (unlock duration and unlock number), sedentary time, sleep duration, number of locations visited, and linear and quadratic academic term week regressors. Random intercepts per subject were included in the model. Each variable was scaled to help with convergence of the REML model and to obtain regression coefficients that can be compared for relative importance. Models inferring interest in COVID fatigue had a better fit (lower deviance) than models of coronavirus interest. All variables were significantly associated with interest in the search term "coronavirus", and all variables except distance traveled were significantly associated with COVID fatigue interest. In both models, phone usage (unlock duration) had the largest positive standardized coefficient, followed by sedentary time. The number of locations visited had the largest magnitude negative standardized coefficient, followed by the number of phone unlocks and sleep duration ($P<.001$).

In the second set of models of interest data, we again made inferences with mobile sensing features, this time with the addition of self-reported anxiety and depression scores. Again, all variables seem to produce a better fit when inferring interest in COVID fatigue. When anxiety and depression were added to the previously used sensing model, our model observed that increased anxiety and depression were significantly associated with a rising interest in coronavirus and COVID fatigue ($P < .001$). Again, we observed increased phone usage (unlock duration), increased sedentary time, and a decreased number of locations visited, with standardized beta weights stable across both models. Sleep was negatively associated with interest in COVID fatigue ($P = .05$), but no longer had a significant association with coronavirus interest, perhaps due to the weekly measured mental health metrics accounting for variance. Notably, both linear and quadratic term week variables were positively associated with covid fatigue interest, though only quadratic term week variables were positively associated with coronavirus interest. A coefficient plot depicting the relative impacts on behaviors and mental health is shown in (Figure 4).

Figure 4. Coefficient plots from mixed linear models of interest in terms “coronavirus” and “COVID fatigue”, inferred by mobile smartphone features and self-reported mental health. Intercept and random intercepts per subject are not plotted. *, **, and *** represent $P < .05$, .01 and .001 respectively.

Discussion

COVID-19 has impacted billions of lives worldwide, in a variety of ways. The devastating toll on physical health around the globe has led to an incredible body of work around the nature of the pathogen. Similarly, a vast and rapidly expanding body of work explores the mental health and behavioral ramifications of COVID-19. Previous work documents large-scale changes in mental health and behaviors among college students that seem related to the novelty of the pandemic [1,7,9,34–37].

Unfortunately, we remain engaged in a battle against the continued spread of COVID-19, necessitating long-term adherence to physical distancing and other mitigation protocols. While the initial impact of these unprecedented shifts in behaviors has been documented, the effects of the pandemic's longevity are less known. This work uses longitudinal data from a cohort of 217 college students to observe what behavioral and mental health changes are associated with the enduring pandemic. As in previous work, we found increased interest in COVID-19 to be associated with increased depression and behavioral changes. Further linear models showed that, as initial interest in coronavirus increased, participants became more sedentary, visited fewer locations, slept less, used their phones more, and showed increases in anxiety and depression. While initial models suggested an increase in sleep during terms affected by COVID-19, controlling for other sensing variables revealed that students exhibited decreases in sleep as the pandemic endured. Though an increase in distance traveled as coronavirus interest rose was observed, we attribute this to students returning home, as it coincides with Dartmouth College closing its campus. We found that the search term “coronavirus” had a stronger relationship with changes in behaviors and mental health, with the exception of levels of depression. With sustained adherence to “Stay Home and Stay Safe” guidelines implemented by many national and international governments, we found that, as the pandemic endured, students were more sedentary, visited fewer locations (as inferred from GPS tracking), slept less, used their phones more and exhibited increases in anxiety and depression. Notably, over the entire course of the study, self-reported anxiety and depression levels were highest in the week after George Floyd was murdered. Future work should investigate the impact of current events on mental health and behavior.

As in previous work [1], we again observe that COVID-19 is associated with decreased sleep, increased sedentary time, and negative mental health outcomes. Recent work, collected pre-pandemic, suggests that sleep may mediate a relationship between physical activity and stress [38]. An overwhelming body of research supports the claim that increased physical activity is associated with longer, better quality sleep [39–41]. On the other hand, physical inactivity tends to be associated with increased stress [42], and recent work suggests that exercising during the pandemic may help reduce levels of stress [43]. Stress has been implicated in changes in mental health [44,45] and poor sleep [46–48]. Importantly, other work identifies disturbances in sleep and physical activity that coincide with COVID-19 fatigue [12]. While the observed prolonged decreases in sleep may potentially mediate a relationship between sustained decreased physical activity and mental well-being during the pandemic, mental health research currently remains uncertain.

Our finding of sustained increased phone usage during the COVID-19 pandemic presents a quandry. Work prior to the pandemic suggests that smartphone overuse is associated with negative changes in mental health [49]. However, at a time of widespread social distancing, it seems as though smartphones may have a more complex relationship with mental health. Recent research has shown that using smartphones to connect with friends and colleagues may be associated with increased well-being during the pandemic [50]. Moreover, social connection may provide resilience in battling COVID-19 fatigue [51]. Simultaneously, increased phone usage during the pandemic may reflect increased social media usage and negative changes in mental health [50,52]. Given the observance of increased phone usage among college students during the COVID-19 pandemic, future work may seek to uncover the various impacts of phone usage during the pandemic.

Primary takeaways from the models are that individuals are maintaining previously seen changes in behavior and mental health. This suggests the importance of prioritizing communication with loved ones, and emphasizes the benefit of maintaining a regular sleep schedule and physical activity to help improve mental health.

Study Limitations and Future Directions

One possible limitation of this study is the search terms used. While other literature uses covid fatigue to refer to behavioral exhaustion, it is worth noting that similar search terms listed on Google Trends are related to the symptomatology of coronavirus (i.e. fatigue related to virus contraction) rather than a behavioral fatigue. Though our graphs show that interest in covid fatigue begins to increase well into the pandemic, but after interest in coronavirus, it is possible that we are partially capturing interest in symptoms. Still, we observe that behaviors and mental health models interest in “covid fatigue” with a better fit than the term “coronavirus”, suggesting that the gradually building interest in COVID-19 fatigue accurately reflects the continuing phases, while interest in the disease itself reflects the initial phase. Future work may consider identifying trending search terms such as “covid mutation” or “covid vaccine” to help quantify the interest in the continuation of the pandemic, and how that interest may be impacting mental health. Similarly, as vaccines are more widely distributed, using the terms “covid vaccine” and “herd immunity” along with the terms used in the current work could be an effective way to model the impacts of later and (hopefully) final stages of the pandemic on mental health.

While the mobile smartphone sensing data gathered is quite robust, they too have potential limitations. When mobility is decreased, such as during a stay-at-home order, people may not always have their phones with them, which could lead to an overestimation of sedentary time and sleep. Our moderate sample size of 217 total participants across all terms and 212 during the COVID-19 pandemic (97.6%) limits generalizability of the findings. Further, participants may be preferentially accessing larger screens (e.g. tablets, laptops, or televisions), so phone usage (as measured by screen unlock duration or number of unlocks) may underestimate the total amount of screen time. However, we do observe increased phone usage, suggesting that the effect sizes we observe are underestimated. Future work capable of distinguishing different types of screen time during the pandemic would be of high interest, as would work that distinguishes the purposes (i.e. working, watching Netflix, reading) and proportions of screen usage. Further work could also use

smartwatches to improve the measurement of behaviors such as sedentary time and allow for more frequent sampling of phone usage, location and other measures. Additionally, the use of smartwatches could facilitate highly accurate inferences of time spent exercising, sleep and sedentary time, as these watches typically track heart rate. Despite the moderate sample size and potential data inaccuracies, strong significant effects on mental health and behaviors were observed, suggesting robust effects.

Though finding ways to combat COVID-19 fatigue is beyond the scope of the current work, we encourage more research on the subject. Our current work was unable to infer daily changes in mental health, as participants were prompted to respond to weekly, not daily, EMAs. While we presume that college students are likely to be more susceptible to experience pandemic fatigue, we do not directly gather fatigue-related feedback. Future studies may consider addressing fatigue more directly, though should be cautious when choosing metrics of fatigue, as they may also be symptoms of depression (e.g. physical exhaustion, anhedonia, trouble sleeping). Administering EMAs on a daily, rather than weekly, basis could help parse day-to-day changes in mental health related to fatigue. In light of the drastic changes in sedentary time, it is critical to find day-to-day activities and/or routines that may help prevent or reduce fatigue levels. There may be differences in the degree of reported mental health changes between those who spend more time watching television compared to those using social media. Though gathering enough participants may be challenging, using questionnaires to investigate specific behaviors that drive or reduce fatigue levels is critical.

Conclusions

While the long fight against COVID-19 continues, we must further our understanding of its impacts on mental health. This study provides additional insight into mental health and related behaviors during the ongoing COVID-19 pandemic. Using mixed linear models of smartphone mobile sensing and self-reported mental health questions, we were able to infer the initial and ongoing phases of the COVID-19 pandemic, as measured by search term interest in coronavirus and COVID fatigue, and, moreover, validate that participants' mental health and related behaviors changed contemporaneously with relative interest levels in these terms. Increases in depression, anxiety, sedentary time, and phone usage, alongside decreases in sleep and the number of locations visited are significantly associated with the ongoing pandemic. All of these changes seem very similar to those seen during the initial phases of the pandemic. As the virus continues to mutate, future work may attempt to identify behaviors as resilience factors for changes in mental health. Similarly, perhaps work tracking the distribution of vaccines may elucidate a return to pre-COVID-19 pandemic levels in behaviors and mental health.

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References

1. Huckins JF, DaSilva AW, Wang W, Hedlund E, Rogers C, Nepal SK, Wu J, Obuchi M, Murphy EI, Meyer ML, others. Mental health and behavior of college students during the early phases of the covid-19 pandemic: Longitudinal smartphone and ecological momentary assessment study. *Journal of medical Internet research JMIR Publications Inc., Toronto, Canada*; 2020;22(6):e20185.
2. Cucinotta D, Vanelli M. WHO declares covid-19 a pandemic. *Acta Bio Medica: Atenei Parmensis Mattioli* 1885; 2020;91(1):157.
3. Dong E. Hongru du, and lauren gardner. ". An Interactive Web-Based Dashboard to Track COVID-19 in Real Time 2020;30120–1.
4. Cao W, Fang Z, Hou G, Han M, Xu X, Dong J, Zheng J. The psychological impact of the covid-19 epidemic on college students in china. *Psychiatry research Elsevier*; 2020;287:112934.
5. Hasan N, Bao Y. Impact of “e-learning crack-up” perception on psychological distress among college students during covid-19 pandemic: A mediating role of “fear of academic year loss”. *Children and Youth Services Review Elsevier*; 2020;118:105355.
6. Zhang Y, Zhang H, Ma X, Di Q. Mental health problems during the covid-19 pandemics and the mitigation effects of exercise: A longitudinal study of college students in china. *International journal of environmental research and public health Multidisciplinary Digital Publishing Institute*; 2020;17(10):3722.
7. Wang Z-H, Yang H-L, Yang Y-Q, Liu D, Li Z-H, Zhang X-R, Zhang Y-J, Shen D, Chen P-L, Song W-Q, others. Prevalence of anxiety and depression symptom, and the demands for psychological knowledge and interventions in college students during covid-19 epidemic: A large cross-sectional study. *Journal of affective disorders Elsevier*; 2020;275:188–193.
8. Liu X, Liu J, Zhong X. Psychological state of college students during covid-19 epidemic. Available at SSRN 3552814 2020;
9. Jacobson NC, Lekkas D, Price G, Heinz MV, Song M, O'Malley AJ, Barr PJ. Flattening the mental health curve: COVID-19 stay-at-home orders are associated with alterations in mental health search behavior in the united states. *JMIR Mental Health [Internet] JMIR Publications Inc.* 2020 Jun;7(6):e19347. [doi: [10.2196/19347](https://doi.org/10.2196/19347)]
10. Harvey N. Behavioral fatigue: Real phenomenon, naïve construct, or policy contrivance? *Frontiers in Psychology Frontiers Media SA*; 2020;11.
11. Bartoszek A, Walkowiak D, Bartoszek A, Kardas G. Mental well-being (depression, loneliness, insomnia, daily life fatigue) during covid-19 related home-confinement—a study from poland. *International journal of environmental research and public health Multidisciplinary Digital Publishing Institute*; 2020;17(20):7417.

12. Field T, Mines S, Poling S, Diego M, Bendell D, Veazey C. COVID-19 lockdown fatigue. *American Journal of Psychiatric Research and Reviews* 2021;4(1):27–27.
13. Rahmandad H, Lim TY, Sterman J. Behavioral dynamics of covid-19: Estimating under-reporting, multiple waves, and adherence fatigue across 92 nations. *medRxiv Cold Spring Harbor Laboratory Press*; 2021;2020–06.
14. Morgul E, Bener A, Atak M, Akyel S, Aktaş S, Bhugra D, Ventriglio A, Jordan TR. COVID-19 pandemic and psychological fatigue in turkey. *The International Journal of Social Psychiatry* SAGE Publications; 2020;
15. Carlucci L, D'Ambrosio I, Balsamo M. Demographic and attitudinal factors of adherence to quarantine guidelines during covid-19: The italian model. *Frontiers in Psychology* Frontiers; 2020;11:2702.
16. Ye B, Zhou X, Im H, Liu M, Wang XQ, Yang Q. Epidemic rumination and resilience on college students depressive symptoms during the COVID-19 pandemic: The mediating role of fatigue. *Frontiers in Public Health* [Internet] Frontiers Media SA; 2020 Dec;8. [doi: [10.3389/fpubh.2020.560983](https://doi.org/10.3389/fpubh.2020.560983)]
17. Hoerger M, Alonzi S, Perry LM, Voss HM, Easwar S, Gerhart JI. Impact of the covid-19 pandemic on mental health: Real-time surveillance using google trends. *Psychological Trauma: Theory, Research, Practice, and Policy* Educational Publishing Foundation; 2020;12(6):567.
18. Tana JC, Kettunen J, Eirola E, Paakkonen H. Diurnal variations of depression-related health information seeking: Case study in finland using google trends data. *JMIR mental health* JMIR Publications Inc., Toronto, Canada; 2018;5(2):e43.
19. Shiffman S, Stone AA, Hufford MR. Ecological momentary assessment. *Annu Rev Clin Psychol Annual Reviews*; 2008;4:1–32.
20. Fried EI. Mental health and social contact during the covid-19 pandemic: An ecological momentary assessment study. *PsyArXiv*; 2020;
21. StudentLife study [Internet]. Available from: <https://studentlife.cs.dartmouth.edu/> [
22. Wang R, Chen F, Chen Z, Li T, Harari G, Tignor S, Zhou X, Ben-Zeev D, Campbell AT. StudentLife: Assessing mental health, academic performance and behavioral trends of college students using smartphones. *Proceedings of the 2014 acm international joint conference on pervasive and ubiquitous computing* 2014. pp. 3–14.
23. Huckins JF, DaSilva AW, Wang R, Wang W, Hedlund EL, Murphy EI, Lopez RB, Rogers C, Holtzheimer PE, Kelley WM, others. Fusing mobile phone sensing and brain imaging to assess depression in college students. *Frontiers in neuroscience* Frontiers; 2019;13:248.
24. Kroenke K, Spitzer RL, Williams JB, Löwe B. An ultra-brief screening scale for anxiety and depression: The phq-4. *Psychosomatics* Elsevier; 2009;50(6):613–621.

25. ActivityRecognitionApi. Google's api for android [Internet]. Available from: <https://developers.google.com/android/reference/com/google/android/gms/location/ActivityRecognitionApi>
26. Wang R, Aung MS, Abdullah S, Brian R, Campbell AT, Choudhury T, Hauser M, Kane J, Merrill M, Scherer EA, others. CrossCheck: Toward passive sensing and detection of mental health changes in people with schizophrenia. Proceedings of the 2016 acm international joint conference on pervasive and ubiquitous computing 2016. pp. 886–897.
27. Developer A. IOS core motion [Internet]. Available from: <https://developer.apple.com/reference/coremotion>
28. Daszykowski M, Walczak B. Density-based clustering methods. Elsevier; 2009;
29. Developer G. Google trends [Internet]. Available from: <https://www.google.com/trends>
30. Bates D, Mächler M, Bolker B, Walker S. Fitting linear mixed-effects models using lme4. Journal of Statistical Software [Internet] Foundation for Open Access Statistics; 2015;67(1). [doi: [10.18637/jss.v067.i01](https://doi.org/10.18637/jss.v067.i01)]
31. Kuznetsova A, Brockhoff PB, Christensen RH, others. LmerTest package: Tests in linear mixed effects models. Journal of statistical software 2017;82(13):1–26.
32. Wickham H. Ggplot2. Wiley Interdisciplinary Reviews: Computational Statistics Wiley Online Library; 2011;3(2):180–185.
33. Hlavac M. Stargazer: Well-formatted regression and summary statistics tables. Bratislava, slovakia: Central european labour studies institute (celsi). 2018.
34. Elmer T, Mepham K, Stadtfeld C. Students under lockdown: Comparisons of students' social networks and mental health before and during the covid-19 crisis in switzerland. Plos one Public Library of Science San Francisco, CA USA; 2020;15(7):e0236337.
35. Gallè F, Sabella EA, Ferracuti S, De Giglio O, Caggiano G, Protano C, Valeriani F, Parisi EA, Valerio G, Liguori G, others. Sedentary behaviors and physical activity of italian undergraduate students during lockdown at the time of covid- 19 pandemic. International journal of environmental research and public health Multidisciplinary Digital Publishing Institute; 2020;17(17):6171.
36. Savage MJ, James R, Magistro D, Donaldson J, Healy LC, Nevill M, Hennis PJ. Mental health and movement behaviour during the covid-19 pandemic in uk university students: Prospective cohort study. Mental Health and Physical Activity Elsevier; 2020;19:100357.
37. Wang X, Hegde S, Son C, Keller B, Smith A, Sasangohar F. Investigating mental health of us college students during the covid-19 pandemic: Cross-sectional survey study. Journal of medical Internet research JMIR Publications Inc., Toronto, Canada; 2020;22(9):e22817.
38. Zhai X, Wu N, Koriyama S, Wang C, Shi M, Huang T, Wang K, Sawada SS, Fan X. Mediating effect of perceived stress on the association between physical activity and sleep quality

among chinese college students. International Journal of Environmental Research and Public Health Multidisciplinary Digital Publishing Institute; 2021;18(1):289.

39. Kredlow MA, Capozzoli MC, Hearon BA, Calkins AW, Otto MW. The effects of physical activity on sleep: A meta-analytic review. Journal of behavioral medicine Springer; 2015;38(3):427–449.

40. Lang C, Brand S, Feldmeth AK, Holsboer-Trachsler E, Pühse U, Gerber M. Increased self-reported and objectively assessed physical activity predict sleep quality among adolescents. Physiology & behavior Elsevier; 2013;120:46–53.

41. Loprinzi PD, Cardinal BJ. Association between objectively-measured physical activity and sleep, nhanes 2005–2006. Mental Health and Physical Activity Elsevier; 2011;4(2):65–69.

42. Zhai X, Ye M, Wang C, Gu Q, Huang T, Wang K, Chen Z, Fan X. Associations among physical activity and smartphone use with perceived stress and sleep quality of chinese college students. Mental Health and Physical Activity Elsevier; 2020;18:100323.

43. Deng C-H, Wang J-Q, Zhu L-M, Liu H-W, Guo Y, Peng X-H, Shao J-B, Xia W. Association of web-based physical education with mental health of college students in wuhan during the covid-19 outbreak: Cross-sectional survey study. Journal of medical Internet research JMIR Publications Inc., Toronto, Canada; 2020;22(10):e21301.

44. Van Praag H. Can stress cause depression? Progress in Neuro-Psychopharmacology and Biological Psychiatry Elsevier; 2004;28(5):891–907.

45. Huckins JF, DaSilva AW, Hedlund EL, Murphy EI, Rogers C, Wang W, Obuchi M, Holtzheimer PE, Wagner DD, Campbell AT. Causal factors of anxiety and depression in college students: Longitudinal ecological momentary assessment and causal analysis using peter and clark momentary conditional independence. JMIR mental health JMIR Publications Inc., Toronto, Canada; 2020;7(6):e16684.

46. Caldwell K, Harrison M, Adams M, Quin RH, Greeson J. Developing mindfulness in college students through movement-based courses: Effects on self-regulatory self-efficacy, mood, stress, and sleep quality. Journal of American College Health Taylor & Francis; 2010;58(5):433–442.

47. Lee S-Y, Wuertz C, Rogers R, Chen Y-P. Stress and sleep disturbances in female college students. American journal of health behavior PNG Publications; 2013;37(6):851–858.

48. Amaral AP, Soares MJ, Pinto AM, Pereira AT, Madeira N, Bos SC, Marques M, Roque C, Macedo A. Sleep difficulties in college students: The role of stress, affect and cognitive processes. Psychiatry research Elsevier; 2018;260:331–337.

49. Demirci K, Akgönül M, Akpinar A. Relationship of smartphone use severity with sleep quality, depression, and anxiety in university students. Journal of behavioral addictions Akadémiai Kiadó; 2015;4(2):85–92.

50. Sun R, Rieble C, Liu Y, Sauter D. Connected despite covid-19: The role of social interactions and social media for wellbeing. PsyArXiv; 2020;
51. Nitschke JP, Forbes PA, Ali N, Cutler J, Apps MA, Lockwood PL, Lamm C. Resilience during uncertainty? Greater social connectedness during covid-19 lockdown is associated with reduced distress and fatigue. British Journal of Health Psychology Wiley Online Library; 2020;
52. Gao J, Zheng P, Jia Y, Chen H, Mao Y, Chen S, Wang Y, Fu H, Dai J. Mental health problems and social media exposure during covid-19 outbreak. Plos one Public Library of Science San Francisco, CA USA; 2020;15(4):e0231924.