Rise in Use of Digital Mental Health Tools and Technologies in the U.S. During the COVID-19 Pandemic

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Abstract

Background: Accompanying the rising rates of reported mental distress during the coronavirus disease 2019 (COVID-19) pandemic has been a reported increase by the media in use of digital technologies to manage health generally, and mental health more specifically.

Objective: The objective of the study was to systematically examine COVID-19 pandemic-related increase in self-reported use of digital mental health tools and other technologies to manage mental health.

Methods: We analyzed results from a national survey of 5,907 individuals in the U.S. using Amazon Mechanical Turk (MTurk) collected across all 50 states and Washington D.C. during four week-long periods in April, May, June, and July of 2020. The first set of analyses employed two different logistic regression models to estimate the likelihood of having symptoms indicative of clinical depression and anxiety, respectively, as a function of the rate of COVID-19 cases per ten people and survey time point. The second set employed seven different logistic regression models to estimate the likelihood of using seven different types of digital mental health tools and other technologies to manage one's mental health, as a function of symptoms indicative of clinical depression and anxiety, rate of COVID-19 cases per ten people, and survey time point. These models also examined potential interactions between symptoms of clinical depression and anxiety, respectively, and rate of COVID-19 cases. All models controlled for respondent sociodemographic characteristics and state fixed-effects.

Results: Higher COVID-19 case rates were associated with a significantly greater likelihood of reporting clinically meaningful symptoms of depression (odds ratio (OR)=2.1, 95% confidence interval (95%CI)=[1.3,3.5]), but not anxiety (OR=1.2, 95%CI=[0.8,1.9]). Survey time point, a proxy for time, was associated with a greater likelihood of reporting clinically meaningful symptoms of depression and anxiety (OR=1.2, 95%CI=[1.1,1.3] and OR=1.1, 95%CI=[1.0,1.2]), respectively). Reported symptoms of depression and anxiety were associated with a greater likelihood of using each type of technology. Higher COVID-19 case rates were associated with a significantly greater likelihood of using mental health forums, websites, or apps (OR=2.8, 95%CI=[1.5,5.2]), and other health forums, websites, or apps (OR=2.7,95%CI=[1.6,4.5]). Time was associated with

increased odds of reported use of mental health forums, websites, or apps (OR=1.2, 95% CI=[1.1,1.3]), phone-based or text-based crisis lines (OR=1.2, 95%CI=[1.1,1.3]); and online, computer, or console gaming/video gaming (OR=1.1, 95%CI=[1.0,1.2]). Interactions between COVID-19 case rate and mental health symptoms were not significantly associated with any of the technology types.

Conclusions: Findings suggested increased use of digital mental health tools and other technologies over time during the early stages of the COVID-19 pandemic. As such, additional effort is urgently needed to consider the quality of these products, either by ensuring users have access to evidence-based and evidence-informed technologies and/or providing them with the skills to make informed decisions around their potential efficacy.

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Abstract

Background:

Accompanying the rising rates of reported mental distress during the coronavirus disease 2019 (COVID-19) pandemic has been a reported increase by the media in use of digital technologies to manage health generally, and mental health more specifically.

Objective:

The objective of the study was to systematically examine COVID-19 pandemic-related increase in self-reported use of digital mental health tools and other technologies to manage mental health.

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We analyzed results from a survey of 5,907 individuals in the U.S. using Amazon Mechanical Turk (MTurk) collected across all 50 states and Washington D.C. during four week-long periods in 2020. The first set of analyses employed two different logistic regression models to estimate the likelihood of having symptoms indicative of clinical depression and anxiety, respectively, as a function of the rate of COVID-19 cases per ten people and survey time point. The second set employed seven different logistic regression models to estimate the likelihood of using seven different types of digital mental health tools and other technologies to manage one's mental health, as a function of symptoms indicative of clinical depression and anxiety, rate of COVID-19 cases per ten people, and survey time point. These models also examined potential interactions between symptoms of clinical depression and anxiety, respectively, and rate of COVID-19 cases. All models controlled for respondent sociodemographic characteristics and state fixed effects.

Results:

Higher COVID-19 case rates were associated with a significantly greater likelihood of reporting symptoms of depression (odds ratio (OR)=2.06, 95% confidence interval (95% CI)=[1.27,3.35]), but not anxiety (OR=1.21, 95% CI=[0.77,1.88]). Survey time point, a proxy for time, was associated with a greater likelihood of reporting clinically meaningful symptoms of depression and anxiety (OR=1.19, 95% CI=[1.12,1.27] and OR=1.12, 95% CI=[1.05,1.19], respectively). Reported symptoms of depression and anxiety were associated with a greater likelihood of using each type of technology. Higher COVID-19 case rates were associated with a significantly greater likelihood of using mental health forums, websites, or apps (OR=2.70, 95% CI=[1.49,4.88]), and other health forums, websites, or apps (OR=2.60, 95% CI=[1.55,4.34]). Time was associated with increased odds of reported use of mental health forums, websites, or apps (OR=1.20, 95% CI=[1.11,1.30]), phone-based or text-based crisis lines (OR=1.20, 95% CI=[1.10,1.31]); and online, computer, or console gaming/video gaming (OR=1.12, 95% CI=[1.05,1.19]). Interactions between COVID-19 case rate

and mental health symptoms were not significantly associated with any of the technology types.

Conclusions:

Findings suggested increased use of digital mental health tools and other technologies over time during the early stages of the COVID-19 pandemic. As such, additional effort is urgently needed to consider the quality of these products, either by ensuring users have access to evidence-based and evidence-informed technologies and/or providing them with the skills to make informed decisions around their potential efficacy.

Keywords: COVID-19; digital technology; mhealth; mental health; depression; anxiety; MTurk

1.0 Introduction

On March 11, 2020, the World Health Organization designated the Coronavirus disease 2019 (COVID-19) outbreak a global pandemic, which has led to unprecedented hazards to mental health globally.[1] By March 2020, individual states within the U.S. began to implement measures to contain the spread of the virus, including limiting travel, mandating physical distancing, and limiting non-essential medical visits. By April of 2020, nearly 200,000 cases of COVID-19 and more than 5,000 deaths had been reported in the U.S.[2]

In addition to the unpredictability and uncertainty of the pandemic itself, policy efforts to mitigate risk, such as “stay at home” orders and/or social distancing, introduced a number of additional stressors including social isolation, inactivity, loss of income, and lack of access to basic services, to name but a few.[3] This may be why, mirroring the increase in COVID-19 cases and deaths, there has been an increase in mental distress.[1, 4-6] For example, data from the U.S. Census Bureau demonstrated that adults assessed as part of a nationally representative survey during in April and May 2020 were more than three times as likely to screen positive for depressive disorders, anxiety disorders, or both, relative to a comparable sample in 2019.[7] In a similar vein, the Centers for Disease Control and Prevention reported significantly elevated levels of adverse mental health

conditions, substance use, and suicidal ideation resulting from the COVID-19 pandemic, with these mental health conditions disproportionately affecting specific populations, such as young adults, Hispanic persons, Black persons, essential workers, unpaid caregivers for adults, and those receiving treatment for preexisting psychiatric conditions.[8]

As medical systems, including those that address mental health, quickly pivoted to digital platforms such as video/phone conferencing and patient-provider text messaging,[9] the documented growth in and reliance on e-Health/tele-health use emerged as a viable solution to continue providing health and mental health services.[10-12] Indeed, it has been suggested that the COVID-19 pandemic is serving as a "black swan" moment for mental health care—an unforeseen event that will permanently shift mental health care provision towards online prevention, treatment, and care in the near future.[12] Given the increase in mental health issues resulting from the pandemic, digital platforms also offer the potential to provide scalable mental health resources, as they may be less reliant on trained providers and are non-consumable.[13] A non-consumable treatment is one that once used retains its therapeutic potential. Unlike a dose of medication, that once used will not benefit another person, digital resources can be used by many people and continue to be helpful.[14]

In tandem with this increase in the use of tele-health services and digital platforms, technology companies have also reported increased demand for digital mental health products and therapeutics since the start of the COVID-19 pandemic.[15] However, there have been no empirical studies examining rates of use of these digital mental health products and therapeutics during the COVID-19 pandemic. Examination of marketplace trends through app analytics platforms (e.g. App Annie) indicate that downloads and engagement have increased since the onset of COVID-19.[16] However, it is unclear if reported rates of growth relate to the pandemic or represent an already documented gradual trend of engagement.[17] In light of the transformative changes that have occurred in the delivery of health and mental health care resulting from the COVID-19 pandemic, understanding potential changes in consumer behavior pertaining to the use of digital mental health

tools and other technologies during the COVID-19 pandemic is needed.

Current Study

To this end, this study examined the following questions: (1) To what extent was the likelihood of having symptoms indicative of clinical depression and anxiety associated with the county COVID-19 case rate and time? 2) Were individuals with moderate to high self-reported depressive or anxious symptomatology more likely to use digital mental health tools and other technologies compared to individuals who endorsed low depression or anxiety symptom experience? and, (3) If so, did the differences in use among those with high versus low symptom endorsement vary according to the rate of COVID-19 cases?

2. Methods

2.1 Participants and Procedures

Participants were recruited from Amazon Mechanical Turk (MTurk), an online crowdsourcing platform commonly used in behavioral science studies.[18] Survey data collection occurred across all 50 states and Washington D.C. during four one-week periods in April, May, June, and July, starting on approximately the 6th of each month. At the first time point, we aimed to recruit approximately 1,250 people. At each of the following time points, we aimed to recruit approximately 1,750 people.

MTurk allows researchers to collect a large amount of quality data quickly and for relatively little cost.[19-21] In MTurk, requesters are people who post or request tasks (e.g., surveys) to be completed, whereas workers are people who are paid for task completion. Requesters can customize the tasks to be available to certain MTurk workers. MTurk workers are able to read descriptions of tasks and select the tasks they are interested in.

For the purpose of this study, study participants had to meet three eligibility criteria: (1) being at least age 18, (2) currently residing in the U.S., and (3) not having completed the survey in a prior wave. If eligible, participants completed the survey via Qualtrics and received $6 via MTurk as

compensation upon completion. The protocol was approved by the Institutional Review Board (IRB#2019-5406) at the University of California—Irvine.

2.2 Measures

2.2.1 Symptoms Indicative of Clinical Depression and Anxiety

The Patient Health Questionnaire-9 (PHQ-9)[22] is a self-report measure used to assess depressive symptoms. It consists of the nine criteria upon which the diagnosis of major depressive disorder according to the Diagnostic and Statistical Manual of Mental Disorders (DSM-IV) is based. The questionnaire uses a 4-point Likert scale (0 = not at all, 1 = several days, 2 = more than half the days, 3 = nearly every day) to gauge the responses to questions about the participants' mental health over the previous 2-week period. Scores on the PHQ-9 can range from 0 to 27; with 0–4 suggesting no depression symptoms, 5–9 mild symptoms, 10–14 moderate symptoms, 15–19 moderately severe symptoms, and 20-27 more severe depression[23], with a cut-off score of 10 or above being used in this study to indicate the presence of clinically elevated levels of depression symptoms (0= minimal or mild depressive symptomatology; 1= moderate to severe depressive symptomatology). This cut-off has been shown to have high sensitivity (88%) and specificity (88%)[22]. In the present sample, validity was strong (unweighted α=0.92).

The Generalized Anxiety Disorder-7 Questionnaire (GAD-7)[24] was used to assess generalized anxiety disorder. Respondents rate answers (0 = not at all, 1 = several days, 2 = more than half the days, 3 = nearly every day) to seven questions assessing anxiety symptoms experienced over the past two weeks, with score ranges from 0 to 21; with 0–4 suggesting minimal symptoms, 5–9 mild symptoms, 10-14 moderate symptoms, 15-21 severe symptoms. A cut off score of 10 or above was used in this study to indicate the presence of elevated levels of anxiety symptoms (0= minimal to mild anxiety symptomatology; 1= moderate to severe anxiety symptomatology). This cut-off has high sensitivity (89%) and specificity (82%).[24] Validity in the present study was high (unweighted α=0.92).

2.2.2 Digital Mental Health Tools and Other Technologies to Support Mental Health

Participants were asked how frequently (never, rarely, sometimes, often, or always) they used 20 different types of technology in the last 7 days to manage or support their mental health. Responses were dichotomized (0=*never, rarely, sometimes* and 1= *often or always*). The 20 technology types included digital mental health tools: (1) mental health online forums or communities (e.g., Mental Health Forum, BeyondBlue); (2) mental health websites (e.g., NAMI, StudentsAgainstDepression.org); (3) mental health apps (e.g., 7 Cups, Headspace, Moodpath); (4) phone-based or text-based crisis lines (e.g., Crisis Text Line, Suicide Prevention Lifeline); (5) other health online forums or communities (e.g., MyFitnessPal forum); (6) other health websites (e.g., WebMD, WHO); and (7) other health apps (e.g., LoseIt, MapMyRun, Sleep Cycle, Flo). Additionally, participants were also asked about the use of technologies to manage their mental health: (8) social media (e.g., Facebook, Instagram, Twitter, Snapchat, etc.); (9) blogs; (10) online, computer, or console gaming/video gaming; (11) online calendar, checklist, or planner; (12) Word document, notepad, or Google Doc; (13) Spreadsheet or Google Sheet; (14) email; (15) texting or messaging software; (16) video conferencing software. Participants were also given the option of selecting (17) other general online forums or communities, which may include mental health communities (e.g., Reddit) and of writing in (18) other types of websites, (19) other apps, and (20) other types of technologies not listed.[25]

The technologies were collapsed into seven different categories by theme: (1) mental health forums, websites, or apps; (2) phone-based or text-based crisis lines; (3) other health forums, websites, or apps; (4) social media and blogs; (5) online, computer, or console gaming/video gaming; (6) online calendar, checklist, planner, Word document, notepad, Google Doc, Spreadsheet, or Google Sheet; and (7) email, texting or messaging software, or video conferencing software.[25]

2.2.3 County COVID-19 Case Rate

The COVID-19 Data Repository maintained by the Center for Systems Sciences and

Engineering (CSSE) at Johns Hopkins University has provided COVID-19 case count in each county in the U.S. on a daily basis, since January 22, 2020.[2] Using participants' zip codes, the case count in each participant's county on the date each participant began the survey was merged with the data collected from MTurk. The county case count was converted into the rate of cases per ten people by dividing the count by each county's total population and multiplying this number by 10. Total county population was obtained from the U.S. Census Bureau, American Community Survey 2018 5-year estimates. [26]

2.2.4 Survey Time Period

Survey response windows that reflected the states' population sizes were made available during four week-long periods in April, May, June, and July of 2020. As such, this variable also serves as a proxy indicator of time. The time-point variable was treated as a continuous variable in the analyses.

2.2.5 Covariates

Additional variables were included as covariates. These encompassed standard demographic characteristics, including age, sex (1=*male*, 2=*female*), race/ethnicity (1=*non-Hispanic white*, 2=*Latino*, 3=*non-Hispanic Asian*, 4=*non-Hispanic Black or African American*, 5=o*ther*), marital status (1=*married or living with a partner*, 2=*single or not living with a partner*, 3=*separated, divorced, or widowed*), employment status (1=*no change in employment status due to COVID-19*, 2=*reduced hours due to COVID-19*, 3=*lost job due to COVID-19*), income level, and education level (1=*completed high school or less*, 2=*some college or more*). Covariates also included a variable representing state fixed effects.

2.3 Analytic Sample

A total of 6,704 survey responses were collected. After omitting ineligible people due to duplicate or missing MTurk Worker Identification numbers, the total sample included 5,907 participants. Of this group, 2.22% had missing data for at least one question from the PHQ-9 and

1.64% had missing data for at least one question from the GAD-7. Participants' average PHQ-9 and GAD-7 scores were imputed if at least 50% of the scale questions were answered. Less than 5.51% of sociodemographic data were missing. Binary and continuous variables underwent mean imputation. An additional category for missing data was created for all other sociodemographic covariates. Where participants had a missing zip code, but provided their state of residence, the average county case count and the average county population in the participant's state were used to calculate the county case rate per ten people. After mean imputation was executed and missing county case rates were replaced with average rates, the analytic sample included 5,899 individuals.

2.4 Statistical Analyses

Summary statistics were calculated to describe the sociodemographic characteristics and prevalence of anxiety and depression symptoms in the sample. The use of digital mental health tools and other technologies in the sample was also described. Means, standard errors, and proportions were reported.

To examine the extent to which the likelihood of having symptoms indicative of clinical depression and anxiety was associated with the county COVID-19 case rate and time, we estimated two separate logistic regression models, one for each mental health outcome. Adjusted models included age, sex, race/ethnicity, marital status, employment status, income level, education level, and state fixed effects.

To evaluate whether individuals with moderate to high self-reported depressive or anxious symptomatology were more likely to use digital mental health tools and other technologies compared to individuals who endorse low depression or anxiety symptom experience, we estimated seven different logistic regression models, one for each of the technology types defined above. Symptoms of anxiety, symptoms of depression, county case rate per ten people, and time point were the independent variables. Adjusted models included age, sex, race/ethnicity, marital status, education level, income level, and state fixed effects. To descriptively assess use of digital mental health tools

and other technologies over time, the predicted probabilities of employing each type of tool or technology were plotted at each time point, while holding the covariates at their mean values. We also plotted the total number of respondents using each type of technology at each time point.

Finally, to understand if differences in use among those with high versus low symptom endorsement varied according to the rate of COVID-19 cases, we further tested the inclusion of two interactions examining the following: 1) county-level COVID-19 case rate with depression and 2) county-level COVID-19 case rate with anxiety in these adjusted models.

Probability weights were generated to account for over- and under-sampling of participants in each state. Use of probability weights allowed for the proportion of participants from each state to reflect the proportion of the U.S. population that each state population comprises. Weights were generated using data from the American Community Survey 2018 5-year estimates of state populations by the 2018 5-year estimate of the U.S. population. Survey weights were employed when estimating summary statistics and multivariable regression. Additionally, a Šidák-corrected cut-off p-value ($P<0.0037$) was employed to identify significant findings and account for the increased Type 1 error rate that resulted from the use of multiple models.[27] All analyses were conducted in Stata 16.[28]

3.0 Results

Table 1 shows the weighted means and standard errors for continuous variables, as well as the weighted proportions of individuals within each categorical variable group. Overall, the average age was 36.99, most of the sample was male, non-Hispanic white, and married, or living in a marital-like relationship. Most of the sample did not experience a change in employment status due to the COVID-19 pandemic, had an income level greater than $50,000, and had greater than a high school education. Close to half of the sample experienced symptoms indicative of clinical levels of depression (45.45%) or anxiety (40.04%).

Table 1.

Characteristics of analytic sample (N=5,899)

Sociodemographics	Mean (SE)
County case rate per ten people	0.069 (0.0023)
Age	36.99 (0.17)
	%
Symptoms of Depression	45.45
Symptoms of Anxiety	40.04
Sex	
Male	57.58
Female	42.42
Race/Ethnicity	
Non-Hispanic white	61.07
Latino	11.69
Asian	6.54
Black/African American	7.85
Other	12.85
Marital Status	
Married/living in a marital-like relationship	62.20
Single/never married	31.76
Separated, divorced, or widowed	6.04
Employment Status	
No change in employment status due to COVID-19	64.42
Reduced hours due to COVID-19	26.88
Lost job due to COVID-19	8.70
Income Level	
0-10,000	4.67
10,001-20,000	7.42
20,001-30,000	11.71
30,001-40,000	11.91
40,001-50,000	11.85
50,001-60,000	12.14
60,001-70,000	8.75
70,001-80,000	8.60
80,001-90,000	5.24
90,001-100,000	6.14
100,000+	11.56
Education Level	
High school or less	19.35
More than high school	80.65
Use of Digital Mental Health Tools and Other Technologies to Manage Mental Health	%
Mental health forums, websites, or apps	27.39
Phone-based or text-based crisis lines	17.74
Other health forums, websites, or apps	34.48
Social media or blogs	47.73
Online, computer, or console gaming/video gaming	33.55
Online calendar, checklist, planner, Word document, notepad, Google Doc, Spreadsheet, or Google Sheet	44.55
Email, texting or messaging software, or video conferencing software	55.50

Note. Proportion of missing data ranged from 0.0-5.51%.

Table 2 shows the results of the two adjusted models regressing the prevalence of clinically meaningful symptoms of depression and anxiety, respectively, on the county COVID-19 case rate per ten people, time point, and the covariates. As shown, COVID-19 case rate was significantly associated with an increase in the likelihood of experiencing clinically meaningful symptoms of depression (odds ratio (OR)=2.06, 95% confidence interval (95% CI)=[1.27,3.35]), but not anxiety (OR=1.21, 95% CI=[0.77,1.88]). Additionally, the likelihood of experiencing symptoms of depression or symptoms of anxiety increased over time (OR=1.19, 95% CI= [1.12,1.27] and OR=1.12, 95% CI= [1.05,1.19], respectively). Results associated with each covariate are shown in Multimedia Appendix 1.

Table 2.

Association Between Symptoms Indicative of Clinical Levels of Depression and Anxiety and Rates of COVID-19 Cases and Time: Estimates Based on Two Separate Logistic Models

	Model 1: Symptoms of Depression (n=5,899)	Model 2: Symptoms of Anxiety (n=5,899)
	OR [95% CI]	OR [95% CI]
County-level COVID-19 case rate per ten people	2.06*	1.21
	[1.27,3.35]	[0.77,1.88]
Survey Time Point	1.19**	1.12**
	[1.12,1.27]	[1.05,1.19]

Notes. Models adjusted for the following covariates: age, sex, race/ethnicity, marital status, employment status, income level, education level, and fixed state effects
ǂ*P*<0.05, **P*<0.0037 (Šidák-corrected p-value), ***P*<0.001

The adjusted association between depression, anxiety, county case rate per ten people, time point, and use of each of the seven categories of digital mental health tools and other technologies is presented in Table 3. Results pertaining to each covariate are shown in Multimedia Appendix 1. Both symptoms of depression and anxiety were significantly associated with the likelihood of using each type of tool and technology. Those with depressive symptoms were three to six times more likely to

use digital mental health tools than those without depressive symptoms. Those with symptoms of anxiety were two to three times more likely to use digital mental health tools than those without symptoms of anxiety. Specifically, those with depressive symptoms or symptoms of anxiety were more likely than those without symptoms to use mental health forums, websites, or apps (OR=6.01, 95% CI=[4.70,7.70] and OR=2.95, 95%, CI=[2.37,3.66], respectively); phone-based or text-based crisis lines (OR=4.98, 95% CI=[3.66,6.77] and OR=2.85, 95% CI=[2.22,3.66], respectively); and other health forums, websites, or apps (OR=3.44, 95% CI=[2.81,4.20] and OR=2.55, 95% CI=[2.11,3.10], respectively).

The findings pertaining to digital mental health tools mirrored the results from models assessing use of other technologies not necessarily related to health. Specifically, those with symptoms indicative of depression and anxiety were more likely, as compared to those without symptoms, to engage in use of social media and blogs (OR=1.56, 95% CI=[1.31,1.86] and OR=1.80, 95% CI=[1.51,2.14], respectively); online, computer, or console gaming/video gaming (OR=1.63, 95% CI=1.36,1.95] and OR=1.67, 95% CI=[1.40,1.99], respectively); online calendar, checklist, planner, Word document, notepad, Google Doc, Spreadsheet, or Google Sheet (OR=1.91, 95% CI=[1.60,2.28] and OR=2.09, 95% CI=[1.75, 2.50], respectively); and email, texting or messaging software, or video conferencing software (OR=1.66, 95% CI=[1.39,1.98] and OR=1.82, 95% CI=[1.52,2.17], respectively). However, in general, even though significant, the odds ratios for these other technologies tended to be much smaller, with the largest being 2.09 and all others below 2.00, while all the odds ratios for the mental health technologies were well above 2.00, ranging from 2.55 to 6.01.

With regard to the association between county-level COVID-19 case rate and digital mental health tool and other technology use, higher county case rate per ten people was associated with increased likelihood of using digital mental health tools, specifically mental health forums, websites, or apps (OR=2.70, 95% CI=[1.49,4.88]) and other health forums, websites, or apps (OR=2.60, 95%

CI=[1.55,4.34]). Additionally, over time, there was an increase in the likelihood of using mental health forums, websites, or apps (OR=1.20, 95% CI=[1.11,1.30]); phone-based or text-based crisis lines (OR=1.20, 95% CI=[1.10,1.31]); other health forums, websites, or apps (OR=1.12, 95% CI=[1.05,1.20]) and online, computer, or console gaming/video gaming (OR=1.12, 95% CI=1.05,1.19]). The predicted probabilities of using each type of technology at each time point while holding the covariates at their mean values are graphed in Multimedia Appendix 2. Multimedia Appendix 3 shows the total number of respondents using each type of technology at each time point.

Table 3.

Associations between Use of Digital Mental Health Tools and Other Technologies and Prevalence of Mental Illness Symptoms and the Rate of COVID-19 Cases: Estimates Based on Seven Separate Logistic Models

	Model 1: Mental health forums, websites, or apps (n=5,849)	Model 2: Phone-based or text-based crisis lines (n=5,831)	Model 3: Other health forums, websites, or apps (n=5,854)	Model 4: Social Media and Blogs (n=5,788)
	OR [95% CI]	OR [95% CI]	OR [95% CI]	OR [95% CI]
Symptoms of Depression	6.01** [4.70,7.70]	4.98** [3.66,6.77]	3.44** [2.81,4.20]	1.56** [1.31,1.86]
Symptoms of Anxiety	2.95** [2.37,3.66]	2.85** [2.22,3.66]	2.55** [2.11,3.10]	1.80** [1.51,2.14]
County-level COVID-19 case rate per ten people	2.70* [1.49,4.88]	1.81‡ [1.02,3.19]	2.60** [1.55,4.34]	1.49 [0.95,2.36]
Survey Time Point	1.20** [1.11,1.30]	1.20** [1.10,1.31]	1.12* [1.05,1.20]	1.08‡ [1.02,1.15]

	Model 5: Online, computer, or console gaming/video gaming (n=5,866)	Model 6: Online calendar, checklist, planner, Word document, notepad, Google Doc, Spreadsheet, or Google Sheet (n=5,835)	Model 7: Email, texting or messaging software, or video conferencing software (n=5,849)

	OR [95% CI]	OR [95% CI]	OR [95% CI]
Symptoms of Depression	1.63** [1.36,1.95]	1.91** [1.60,2.28]	1.66** [1.39,1.98]
Symptoms of Anxiety	1.67** [1.40,1.99]	2.09** [1.75,2.50]	1.82** [1.52,2.17]
County-level COVID-19 case rate per ten people	1.65ǂ [1.07,2.56]	2.04ǂ [1.26,3.30]	1.77ǂ [1.09,2.89]
Survey Time Point	1.12** [1.05,1.19]	1.08ǂ [1.01,1.15]	1.08ǂ [1.02,1.14]

Notes. Models adjusted for the following covariates: age, sex, race/ethnicity, marital status, employment status, income level, education level, and fixed state effects.
ǂ $P<0.05$, * $P<0.003$ (Šidák-corrected p-value), ** $P<0.001$

Lastly, models assessing the interaction of county-level COVID-19 case rate and symptoms indicative of anxiety or depression did not yield significant findings (analyses available on request). For this reason, interaction terms were not subject to further analyses.

4.0 Discussion

To our knowledge, this is the first study to examine rates of use of digital mental health tools and other technologies to manage one's mental health among a sample of people living during the early stages of the COVID-19 pandemic. Similar to other studies,[29] rates of COVID-19 cases were associated with increased rates of depressive symptoms. Both depressive and anxiety symptoms and COVID-19 county case rates were associated with the largest increased likelihood of using digital mental health tools, specifically mental health forums, websites, and apps; phone-based/text-based crisis lines; and other health forums, websites, and apps, reflecting the greatest increase in likelihood of use for products designed specifically for health and mental health. Interestingly, we also found a general increase in the likelihood of using other technologies to support one's mental health, including gaming and work products, among those experiencing symptoms of mental illness. This increase in use of other technologies may reflect the transition to working from home that occurred for many people.

We also sought to examine if the likelihood of using these tools and technologies was the

highest among people who were both living in counties with high COVID-19 case rates *and* exhibiting symptoms indicative of clinically meaningful levels of depression or anxiety. The findings suggested, in fact, that there was no additional significant likelihood of increased use among respondents with depressive or anxious symptoms living in counties with high COVID-19 case rates compared to individuals with similar symptom levels in counties with low COVID-19 rates. Of course, it is likely that other factors, such as the impacts of policy measures aimed at mitigating risks —such as physical distancing, work from home, or school closures—may have had a greater impact on mental health symptoms and people turning to digital tools for mental health support. In the absence of in-person connections or services, digital tools might play an important role in combatting the mental health impact of the pandemic.

We also found that the odds of having used these technologies generally increased over time. This increase in use of digital mental health tools and other technologies may be due, in part, to increased access to some of these technologies. For example, cities like New York City[30] have made technologies freely available to their residents, and/or shared recommendations for particular products that have been vetted. Additionally, health insurance companies, such as Kaiser Permanente and others, have also made available mental health products freely available for their enrollees.[31] It might also be due to the fact that people are spending more time interacting with technologies and these may be convenient ways to receive mental health support.

Our findings that people are increasingly using various technologies—both those specifically designed for mental health support as well as those that are not—are consistent with studies that explore the various ways people use technology to self-manage their mental health.[32-34] These findings also support recent calls for understanding how the technology ecosystem might impact mental health and lead to opportunities for prevention and intervention tools.[35] Some efforts, such as Google's integration of mental health screening into their search engine, have been launched.[36] In light of our findings, it appears as though there is consumer interest for such resources. Furthermore,

an important consideration for future work is to ensure that consumers find effective and safe resources, and have the proper support for using such resources appropriately.

Indeed, despite this increased use and interest, evidence-based and safe resources are rarely available for consumers. One study has suggested that only 2.08% of publicly available psychosocial wellness and stress management mobile apps have published, peer-reviewed evidence of feasibility and/or efficacy.[37] Furthermore, few products provide sufficient information to gauge their safety and privacy,[38] and even among those that do, many share information with third-parties in ways that might not be disclosed in those policies.[39] Although various efforts have been launched that either evaluate or offer evaluative frameworks for mental health apps including One Mind PsyberGuide,[40] ORCHA,[41] and the American Psychological Association App Evaluation Framework,[42] no widely accepted or coordinated effort at regulation and evaluation in the U.S. exists, despite multiple calls for such models (see NIH, National Advisory Work Group[43]). Indeed, better regulation and better access to information at point-of-access could be a significant improvement in helping guide consumers,[44] who are demonstrating a clear interest in such resources, and might serve an important need in light of the COVID-19 pandemic.

Several study limitations should be noted. First, this sample was collected from MTurk workers who regularly use the computer, and therefore require the necessary technology, mobility, and digital literacy to participate.[45] This might contribute to the rates of technology use reported and the ability to use technologies—both those designed for mental health and otherwise—to support their mental health. Additionally, it is likely that people with the lowest socio-economic status, the most-isolated, and those with limited access to technology were omitted from the study. These individuals may represent those most affected by COVID-19 and thus may have the greatest mental health needs.[46] Second, the survey was only available in English, and thus the findings may not hold among groups with limited English proficiency who also might be less likely to use these technologies, especially because many are not designed for diverse populations.[47] Third, this study

only included people living in the U.S., and thus, findings cannot be generalized to other countries.[1] Fourth, there exist a number of scales pertaining to examining the self-reported impact of COVID-19 on mental health.[48-51] These works were primarily published during the development and implementation of this survey, and as such, they were not included in the present study. Fifth, there exists the possibility that at least some of the survey responses were bot-generated. To test for the potential influence of bots, we executed post-hoc diagnostics previously suggested by Chmielewski and Kucker.[52] Removing those responses suspected to be bot-generated did not substantially change the findings. Thus, we reported on those findings generated from the full analytic sample. However, we also have included the results garnered after removing tagged responses (results available in Multimedia Appendix 4).

Finally, this study focused on examining the extent to which people used mHealth technologies throughout the early period of the pandemic. The findings do not shed light on the effectiveness these particular strategies for managing mental health. For many, the engagement in digital mental health tool and other technology use has been critical for enhancing social connectedness, managing stress and anxiety, and providing greatly needed entertainment.[53] Although the vast majority of the increase in digital technology use is adaptive, it is important to note that there are likely negative impacts of this growth, including the spread of false information.[54-56] Furthermore, there exist subgroups of vulnerable individuals that are at risk of developing problematic usage patterns.[53] Excessive engagement in specific online activities such as video gaming, social media use, and shopping has been linked with severe problems and elevate the risk of disordered or addictive use.[57, 58]

In conclusion, the present study provides an important description of the prevalence of symptoms of anxiety and depression and digital mental health tool and other technology use during the early stages of the COVID-19 pandemic. Specifically, we found evidence of an increased likelihood of experiencing depressive symptoms both when considering differences between county

COVID-19 case rates and changes over time. Furthermore, COVID-19 case rate and time were all generally associated with an increased likelihood of using digital mental health tools and other technologies. Lastly, those experiencing symptoms of depression or anxiety were more likely than those without symptoms to use tools and technologies to manage their mental health.

As the pandemic is expected to continue well into the spring and summer of 2021, and as depression,[59, 60] anxiety,[7, 61] and suicidal ideation rates continue to climb,[1, 8, 62] the importance of providing easy access to tools and technologies to manage one's mental health will become even more important. Current shortage of mental health professionals demands the need to explore more scalable solutions that might be able to be adapted and deployed to meet the needs of various populations. The findings from this study, as well as future research that may address more specific issues designed to understand how digital mental health tools and other technologies can be more accessible and effective for the populations who need them, could inform public health efforts.

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Author contributions:
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EAJ: Conducted analyses, drafting of manuscript and critical revision of the manuscript

EVE, MS, KD, SMS, NAS, KZ: Study concept and design, feedback on draft of manuscript, critical revision of the manuscript

DS, MN: Feedback on draft of manuscript, critical revision of the manuscript

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Conflicts of Interest:
None declared.
Captions
Multimedia Appendix 1. Regression models employing full sample.
Multimedia Appendix 2. Predicted probability of using a type of digital mental health tool or other technology at each time point when covariates are at their mean values.

Multimedia Appendix 3. Number of participants using a type of digital mental health tool or other technology at each time point.
Multimedia Appendix 4. Regression models employing sample generated after removing responses suspected to be bot-generated.

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Supplementary Files

Multimedia Appendixes

Regression models employing full sample.
URL: http://asset.jmir.pub/assets/c8269795884bcb891214b5f4c4955d06.docx

Predicted probability of using a type of digital mental health tool or other technology at each time point when covariates are at their mean values.
URL: http://asset.jmir.pub/assets/3ae516fb9b841f316a736758079476da.png

Number of participants using a type of digital mental health tool or other technology at each time point.
URL: http://asset.jmir.pub/assets/de44746ac20e4dc980e1323ddb35ca94.png

Regression models employing sample generated after removing responses suspected to be bot-generated.
URL: http://asset.jmir.pub/assets/679f44c33d18175ae5c57d4f42299c86.docx