Attitudes towards COVID-19 mHealth use among Adults with Chronic Health Conditions: A Secondary Data Analysis of the COVID-19 Impact Survey

Marlene Camacho-Rivera, Jessica Yasmine Islam, Argelis Rivera, Denise Christina Vidot

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Table of Contents

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Marlene Camacho-Rivera[1] BS, MS, SCD; Jessica Yasmine Islam[2] BS, MPH, PhD; Argelis Rivera[3] BSc, MPH, MD; Denise Christina Vidot[4] BSc, PhD

[1]SUNY Downstate Health Sciences University BROOKLYN US
[2]University of North Carolina Lineberger Comprehensive Cancer Center Chapel Hill US
[3]Icahn School of Medicine at Mount Sinai New York US
[4]University of Miami School of Nursing and Health Studies Coral Gables US

Corresponding Author:
Marlene Camacho-Rivera BS, MS, SCD
SUNY Downstate Health Sciences University
450 Clarkson Avenue
450 Clarkson Avenue, MSC 43
BROOKLYN
US

Abstract

Background: Adults with chronic conditions are disproportionately burdened by COVID-19 morbidity and mortality. While COVID-19 mobile-health (mHealth) applications have emerged, research examining attitudes towards COVID-19 mHealth use among those with chronic conditions is scarce.

Objective: To examine attitudes and identify determinants of COVID-19 mHealth use across demographic and health-related characteristics; and evaluate associations of having chronic health conditions with attitudes towards COVID-19 mHealth use (e.g. use of mHealth or web-based methods to track COVID-19 exposures, symptoms, and recommendations).

Methods: We utilized nationally-representative data from the COVID-19 Impact Survey collected from April-June 2020 (n=10,760). Chronic conditions were defined using self-reported diagnoses and categorized as cardiometabolic-related, respiratory-related, immune-related, mental health, and overweight/obesity. Primary outcomes were attitudes of COVID-19 mHealth: (1) likelihood of using a mobile-phone app to track COVID-19 symptoms and receive recommendations, (2) likelihood of using a website to track COVID-19 symptoms, location, and receive recommendations, and (3) likelihood of using an app using location to track potential COVID-19 exposure. Response options were categorized into extremely/very likely, moderately likely, or not likely. Multinomial logistic regression was used to compare likelihood of COVID-19 mHealth use across chronic health conditions, with not likely as the reference category for each outcome. We evaluated determinants of each form of COVID-19 mHealth intervention using Poisson regression.

Results: Among the 10,760 respondents, about half were aged 30-59 years, female, had a household income <$50,000, and had employer-sponsored insurance. Overall, 22% were extremely/very likely to use a mobile-phone app or a website to track their COVID-19 symptoms and receive recommendations. Almost one-quarter were extremely/very likely to use a mobile-phone app to track their location and receive push notifications if they have been exposed to COVID-19. When stratified by chronic disease group, we observed that patterns of likelihood of mHealth app use were largely consistent. After adjustment for covariates, adults living with mental health conditions were most likely to report being either extremely/very or moderately likely to use each mHealth intervention when compared to those who were not likely. Adults with respiratory-related chronic diseases were extremely/very (cOR:1.16, 95% CI:1.00-1.35) and moderately likely (cOR:1.23, 95% CI:1.04-1.45) to use a mobile-phone app to track their location and send push notifications if they might have been exposed to COVID-19. Across each mHealth intervention, positive determinants of extremely/very likely use included being female, racial/ethnic minority, and having at least one COVID-19 related symptom within the last seven days.

Conclusions: Our study demonstrates that attitudes towards COVID-19 mHealth use vary widely by modality (web-based vs. app) and across chronic health conditions. These findings may inform adoption of and long-term engagement with COVID-19

apps, a crucial factor for determining their potential to reduce disparities in COVID-19 morbidity and mortality among individuals with chronic health conditions.

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Marlene Camacho-Rivera[1], MPH, ScD; Jessica Y. Islam[2], MPH, PhD; Argelis Rivera[3], MD; Denise Vidot[4], PhD

[1] Department of Community Health Sciences, SUNY Downstate Health Sciences University, Brooklyn NY, United States
[2] University of North Carolina, Lineberger Comprehensive Cancer Center, Chapel Hill, NC United States
[3] Department of Medicine, Icahn School of Medicine at Mount Sinai, New York, NY, United States
[4]University of Miami School of Nursing and Health Studies, Coral Gables, FL, United States

Corresponding Author:
Marlene Camacho-Rivera, ScD MPH
Department of Community Health Sciences
SUNY Downstate Health Sciences University
450 Clarkson Avenue
Brooklyn, NY 11203
United States
Phone: 1 718 270 5266
Email: marlene.camacho-rivera@downstate.edu

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Abstract (450/450)

Background: Adults with chronic conditions are disproportionately burdened by COVID-19 morbidity and mortality. While COVID-19 mobile-health (mHealth) applications have emerged, research examining attitudes towards COVID-19 mHealth use among those with chronic conditions is scarce.

Objective: To examine attitudes and identify determinants of COVID-19 mHealth use across demographic and health-related characteristics; and evaluate associations of having chronic health conditions with attitudes towards COVID-19 mHealth use (e.g. use of mHealth or web-based methods to track COVID-19 exposures, symptoms, and recommendations).

Methods: We utilized nationally-representative data from the COVID-19 Impact Survey collected from April-June 2020 (n=10,760). Primary exposure was a history of chronic conditions which was defined using self-reported diagnoses of cardiometabolic, respiratory, immune-related, mental health conditions, and overweight/obesity. Primary outcomes were attitudes of COVID-19 mHealth including (1) likelihood of using a mobile-phone app to track COVID-19 symptoms and receive recommendations, (2) likelihood of using a website to track COVID-19 symptoms, location, and receive recommendations, and (3) likelihood of using an app using location to track potential COVID-19 exposure. COVID-19 mHealth use outcome response options were extremely/very likely, moderately likely, or not too likely/not likely at all. Multinomial logistic regression was used to compare likelihood of COVID-19 mHealth use across chronic health conditions, with not too likely/not likely at all as the reference category for each outcome. We evaluated determinants of each form of COVID-19 mHealth intervention using Poisson regression.

Results: Among the 10,760 respondents, about half were aged 30-59 years, female, had a household income <$50,000, and had employer-sponsored insurance. Overall, 22% were extremely/very likely to use a mobile-phone app or a website to track their COVID-19 symptoms and receive recommendations. Almost one-quarter were extremely/very likely to use a mobile-phone app to track their location and receive push notifications if they have been exposed to COVID-19. After adjustment for age, race/ethnicity, gender, socioeconomic status, and residence, adults living with mental health conditions were most likely to report being either extremely/very or moderately likely to use each mHealth intervention when compared to those who were not likely. Adults with respiratory-related chronic diseases were extremely/very (cOR:1.16, 95% CI:1.00-1.35) and moderately likely (cOR:1.23, 95% CI:1.04-1.45) to use a mobile-phone app to track their location and send push notifications if they might have been exposed to COVID-19. Across each mHealth intervention, positive determinants of extremely/very likely use included being female, racial/ethnic minority, and having at least one recent COVID-19 related symptom.

Conclusions: Our study demonstrates that attitudes towards COVID-19 mHealth use vary widely by modality (web-based vs. app) and across chronic health conditions. These findings may inform adoption of and long-term engagement with COVID-19 apps, a crucial factor for determining their potential to reduce disparities in COVID-19 morbidity and mortality among individuals with chronic health conditions.

Keywords: mHealth; COVID-19; chronic health conditions; health disparities

Introduction

Since the declaration of the COVID-19 pandemic, in the United States (U.S), over 7 million cases of COVID-19 cases have been identified and more than 200,000 lives have been lost [1]. Public health strategies to reduce the transmission of COVID-19 have included the enactment of policies such as quarantine and social distancing, closures of non-essential businesses, and recommendation of preventive behaviors such as hand washing and wearing of face masks [2,3]. Emerging studies have reported that implementation of policies and adherence to preventive best practices have varied widely geographically and by demographic subgroups [4,5]. Public health and clinical researchers have reported the disproportionate burden of COVID-19 morbidity and mortality among racial and ethnic minorities, the elderly, and individuals with pre-existing chronic health conditions [6–21]. Among both clinical and population-based studies, non-Hispanic Black and Latino individuals and communities have been found at increased risk for COVID-19 exposure

[17,19,20,22], morbidity [8,9,23,24], and mortality [7,25,26]. Numerous chronic health conditions, including hypertension [8,23,26–29], diabetes [11,23,27,28,30], cancer [15,31–33], COPD [34–36] and asthma [28,37–39], and obesity [40–43] have been associated with increased risk for poor COVID-19 outcomes.

Simultaneously, a proliferation of COVID-19 mHealth tools to track COVID-19 statistics, monitor potential COVID-19 symptoms, and reduce the social and mental health impacts of the COVID-19 pandemic have emerged [44–64]. Several COVID-19 apps that have been developed for public health surveillance provide up-to-date statistics including new cases, hospitalizations, and confirmed deaths [46,62,65]. Among apps that allow for real-time symptom monitoring, trackers, and telemedicine systems have helped elucidate the frequency of symptoms associated with COVID-19, allowing patients and providers the opportunity to respond earlier to symptom progression [44,47,48,66]. Reviews of contact tracing apps have highlighted their effectiveness in improving spatiotemporal reporting of new cases, management and follow-up of COVID-19 cases, and education on preventive behaviors [52,53,57,58,67–70]. To address the mental and social impacts of the COVID-19 pandemic, several apps have focused on reducing social isolation, providing positive coping strategies, and monitoring mental health symptoms [55,56,63,71–74]. While researchers have noted the utility of COVID-19 apps in providing education and public health surveillance amidst a rapidly evolving landscape, reviews of COVID-19 apps have highlighted several barriers to the availability, safety, and long-term sustainability of these technologies including cost, use of evidence-based guidelines, and user-centered design considerations in functionalities and content [45,61,75–77]. While differences in user-preferences and perceptions of susceptibility given individual risk factors exist across social and demographic groups, few studies have examined attitudes toward COVID-19 mHealth tools among adults with and without pre-existing health conditions.

Objectives

The aims of this study were (1) to identify differences in attitudes towards COVID-19 mHealth tools across individuals with chronic health conditions; (2) to evaluate associations between having a pre-existing chronic health condition and attitudes towards COVID-19 mobile-based app and website use to track potential COVID-19 exposure and symptoms; and (3) to identify determinants of mHealth intervention use. To accomplish these study objectives, we leveraged publicly available data from the COVID-19 Impact Survey, a nationally representative sample of the U.S. adult population, designed to offer national insights about the American population's experiences during the COVID-19 pandemic.

Methods

COVID-19 Impact Survey Dataset

Data for these analyses were obtained from the publicly available COVID-19 Household Impact Survey, conducted by the non-partisan and objective research organization NORC at the University of Chicago for the Data Foundation. The COVID-19 Household Impact Survey is a philanthropic effort to provide national and regional statistics about physical health, mental health, economic security, and social dynamics in the United States (U.S.) [78]. The survey is designed to provide weekly estimates of the U.S. adult (ages 18 and older) household population nationwide. Currently, data from Week 1 (April 20-26, 2020), Week 2 (May 4-10, 2020), and Week 3 (May 30th-June 8th, 2020) are available, which were merged for this analysis. As the AmeriSpeak® analytic sample of the COVID-19 Impact Survey was derived from de-identified publicly available data, IRB approval was not required for this study.

Funded and operated by NORC at the University of Chicago, AmeriSpeak® is a probability-based panel designed to be representative of the US household population. During the initial recruitment phase of the AmeriSpeak panel for the COVID Impact Survey, randomly selected US households were sampled using area probability and address-based sampling. These sampled households were then contacted by US mail, telephone, and field interviewers (face to face). The panel provides sample coverage of approximately 97% of the U.S. household population. Those excluded from the sample include people with P.O. Box only addresses, some addresses not listed in the USPS Delivery Sequence File, and some newly constructed dwellings. While most AmeriSpeak households participate in surveys via the Internet, households without web access were able to participate in AmeriSpeak surveys by telephone. Interviews were conducted in English and Spanish. Interviews were conducted with adults age 18 and over representing the 50 states and the District of Columbia. Panelists were offered a $5 monetary incentive for completing the survey. The number of participants invited and percentage of interviews completed by week are as follows: 11,133 invited with 19.7% interviews completed (Week 1); 8,570 invited with 26.1% interviews completed (Week 2); and 10, 373 invited with 19.7% interviews completed (Week 3) [78]. The analytic sample includes 10,760 adults nationwide and is weighted to reflect the US population of adults aged 18 years and over. The demographic weighting variables were obtained from the 2020 Current Population Survey.

COVID-19 mHealth Use Attitudes

Our primary outcomes for this analysis were participants' attitudes towards willingness to use COVID-19 mHealth tools to track potential COVID-19 exposure and symptoms. To characterize attitudes towards the use of COVID-19 mHealth tools to track potential COVID-19 exposure, we used participant's responses to the following question:

- "If this option was available to you, how likely would you install an app on your phone that tracks your location and sends push notifications if you might have been exposed to COVID-19"?

To characterize attitudes towards the use of COVID-19 mHealth tools to track potential COVID-19 symptoms and recommendations, we used participant's responses to the following two questions:

- "If this option was available to you, how likely would you use a website to log your symptoms and location and get recommendations about COVID-19?"
- "If this option was available to you, how likely would you install an app on your phone that asks you questions about your own symptoms and provides recommendations about COVID-19?".

For each of the 3 outcomes, response options were extremely likely, very likely, moderately likely, not too likely, and not likely at all; due to small sample sizes, response options for extremely likely and very likely were collapsed into one category and not too likely and not likely at all were collapsed into one category for each outcome.

History of Chronic Health Conditions

The primary predictor for this analysis was participants' self-report of a chronic health condition. Within the survey, participants were asked to reply "yes, no, or not sure" to the following question: "Has a doctor or other health care provider ever told you that you have any of the following: Diabetes; High blood pressure or hypertension; Heart disease, heart attack or stroke; Asthma; Chronic lung disease or COPD; Bronchitis or emphysema; Allergies; a Mental health condition; Cystic fibrosis; Liver disease or end-stage liver disease; Cancer; a Compromised immune system; or Overweight or obesity." Given the small sample sizes reported among certain categories of health conditions, we further aggregated health conditions into the following 5 categories: cardiometabolic (diabetes, high blood pressure, heart disease, heart attack or stroke, liver disease or end-stage liver disease), overweight/obesity, respiratory (allergies, asthma, chronic lung disease or COPD, bronchitis or emphysema), immune-related (cystic fibrosis, cancer, a compromised immune system), and mental health conditions.

Covariates

The following covariates were included in the multivariable analyses: age categories (18-29, 30-44, 45-59, 60+), gender (male, female), race/ethnicity categories (non-Hispanic White, non-Hispanic Black, Hispanic or Latino, Asian, non-Hispanic other), education categories (no high school diploma, high school graduate, some college, baccalaureate or above), residence (rural or urban), and household income (<$50,000, $50,000 – < $100,000, $100,000 or more). These covariates were chosen based on the review of the mHealth disparities literature and COVID-19 disparities literature [5,79–82].

Data Analysis

Descriptive statistics are displayed in percentages among all respondents unless otherwise labeled, and include a margin of error of +/- 3·0 percentage points at the 95% confidence intervals among all adults. Chi-squared tests were used for univariate comparison of categorical variables including age, gender, race/ethnicity, education, income, residence, and chronic health condition. For COVID-19 mHealth outcomes, we used multinomial logistic regression to compare the likelihood of COVID-19 mHealth use across chronic health conditions after adjustment for age, gender, race/ethnicity, education, income, and residence. For each COVID-19 mHealth outcome, we compared the likelihood of COVID-19 mHealth use to participants in the 'not likely to use' group (reference category). To estimate determinants of being extremely/very likely to utilize each COVID-19 mHealth intervention, we computed prevalence ratios with Poisson regression using robust estimation of standard errors.[83–85] Potential variables for inclusion in the model were assessed using available sociodemographic variables and bivariate Poisson regression analysis. Due to the exploratory nature of this analysis using a predictive framework, an arbitrary p-value of <0.10 was used as criteria to include the variable in the multivariable Poisson regression model. For multivariable Poisson regression models, adjusted prevalence ratios (aPR), and 95% confidence intervals (CIs) for each independent variable were calculated.

The Type I error was maintained at 5%. Based on the exploratory nature of this analysis, we did not include an adjustment for multiple comparisons.[86,87] All statistical analyses were conducted using Stata IC 15 (StataCorp LLC, College Station, TX). Sampling weights were applied to provide results that were nationally representative of the U.S. adult population.

Results

COVID-19 Impact Survey Descriptive Results

Table 1 displays the descriptive characteristics of the analytic sample. Sixty-two percent of respondents were non-Hispanic White, 12% non-Hispanic Black, 17% Hispanic, and 9% were of another non-Hispanic race or ethnicity. Ten percent of respondents had less than a high school diploma, 28% had a high school diploma, 28% had some college, and 34% had a baccalaureate degree or more. Twenty-one percent of participants were aged 18-29 years old, 25% were aged 30-44, 24% were aged 45-59, and 30% were age 60 or older. Forty-eight percent of respondents were male and 52% were female. Seventy-two percent of participants lived in urban areas while 28% lived in rural or suburban areas.

History of chronic health conditions ranged from 16% reporting a history of mental health conditions to 43% reporting a history of allergies. The most common chronic health conditions reported were allergies (43%), cardiometabolic diseases (38%), and overweight or obesity (33%). Twenty-two percent of adults reported they were extremely or very likely to install a mobile-phone app to record symptoms and obtain recommendations about COVID-19, and use a website to log their symptoms, location, and receive recommendations about COVID-19. About one-quarter of adults reported they were extremely or very likely to install an app on their phone to track their location and send push notifications if they may have been exposed to COVID-19.

Table 1: Characteristics of COVID Impact Survey respondents (n = 10,760), a nationally representative survey of the US, (April-June 2020)

	Total	
	Col %	95% CI

Age		
18-29	20.5	19.3,21.8
30-44	25.4	24.4,26.5
45-59	24.3	23.2,25.4
60+	29.8	28.6,30.9
Race/Ethnicity		
White, NH	61.6	60.3,62.9
Black, NH	11.9	11.0,12.7
Hispanic	16.5	15.5,17.7
Asian, NH	5.1	4.4,5.8
Other, NH	3.5	3.1,3.9
Sex		
Male	48.3	47.0,49.6
Female	51.7	50.4,53.0
Employed in the past 7 days	49.7	48.4,51.1
Education		
No HS Diploma	9.8	8.8,10.8
HS Graduate	28.2	27.0,29.6
Some College	27.7	26.7,28.7
Baccalaureate or Above	34.3	33.1,35.5
Household Income		
<$50,000	45.8	44.5,47.1
$50,000-<$100,000	32.1	30.9,33.3
≥$100,000	22.1	21.1,23.2
Population Density		
Rural	9.1	8.4,9.8
Suburban	18.8	17.8,19.7
Urban	72.2	71.0,73.3
Insurance Type or Health Coverage Plans		
Purchased Plan	17.4	16.4,18.5
Employer-Sponsored	51.7	50.3,53.0
TRICARE	4.9	4.4,5.4
Medicaid	23.5	22.4,24.7
Medicare	25.3	24.2,26.4
Dually Eligible (Medicare & Medicaid)	9.7	9.0,10.4
VA	4.5	4.0,5.0
Indian Health Service	1.2	0.9,1.6
No insurance	8.8	8.1,9.6
Cardiometabolic-Related Chronic Diseases*	37.8	36.5, 39.0
Respiratory-Related Chronic Diseases†	23.6	22.5, 24.7
Immune-Related Chronic Diseases‡	13.1	12.3, 13.9
Overweight/Obesity	33.1	31.9, 34.3
Mental Health-Related Conditions§	15.5	14.6, 16.4
How likely would you be to participate in:		
Installing an app on your phone that asks you questions about your own symptoms and provides recommendations about COVID-19		
Extremely/Very Likely	21.8	20.7, 22.9

Moderately Likely	20.9	19,8, 22.1
Not too likely/ Not likely at all	57.3	55.9, 58.6
Using a website to log your symptoms and location and get recommendations about COVID-19		
Extremely/Very Likely	21.1	20.1, 22.2
Moderately Likely	23.5	22.3, 24.7
Not likely	55.4	54.1, 56.7
Installing an app on your phone that tracks your location and sends push notifications if you might have been exposed to COVID-19		
Extremely/Very Likely	24.1	22.9, 25.2
Moderately Likely	19.9	18.8, 20.9
Not likely	56.0	54.7, 57.4

*Cardiometabolic: diabetes, high blood pressure, heart disease, liver disease/end-stage liver disease

†Respiratory: Asthma, chronic lung disease/COPD, bronchitis/emphysema

‡Immune: Cystic fibrosis, cancer, a compromised immune system

§Mental Health: a mental health condition

Attitudes towards COVID-19 mHealth Use across Chronic Health Conditions

As displayed in Table 2, differences in attitudes towards the use of COVID-19 mHealth tools emerged across various chronic health conditions. Compared to adults without mental health conditions, adults with a history of mental health conditions were significantly more likely to report potential download and use of an app to track COVID-19 symptoms and recommendations ($p = 0.004$), more likely to report potential download and use of an app to track location and potential COVID-19 exposure ($p < 0.001$), and use of a website to log COVID-19 symptoms and receive recommendations ($p = 0.005$). Compared to non-obese participants, respondents who reported being obese were significantly more likely to report potential download and use of an app to track location and potential COVID-19 exposure ($p = 0.039$). In the univariate analysis, no other significant differences in COVID-19 mHealth attitudes were observed by a history of respiratory conditions or immune-related conditions.

Table 2: Attitudes towards mHealth interventions for COVID-19 testing and tracking to help slow the spread of the virus, stratified by chronic disease group

	Cardiometabolic*-Related Chronic Disease				*P*	Respiratory†-Related Chronic Disease				*P*	Immune‡-Related Chronic Disease				*P*	Mental Health§-Related Chronic Disease			
	No		Yes			No		Yes			No		Yes			No		Yes	
	%	95% CI	%	95% CI		%	95% CI	%	95% CI		%	95% CI	%	95% CI		%	95% CI	%	95% CI
If these options were available to you, how likely would you be to participate in them?																			
Installing an app on your phone that asks you questions about your own symptoms and provides recommendations about COVID-19					0.02					1.00					0.74				
Extremely/Very	20.7	19.4,22.2	23.5	21.7,25.3		21.8	20.6,23.1	21.7	19.5,24.1		21.7	20.5,22.9	22.7	19.8,25.8		21.6	20.4,22.8	22.8	20.2,25.[illegible]
Moderately	21.8	20.3,23.3	19.5	17.9,21.2		20.9	19.6,22.2	21.0	18.7,23.4		20.9	19.7,22.1	21.3	18.7,24.2		20.2	19.0,21.5	24.7	21.8,27.[illegible]
Not likely	57.5	55.7,59.2	57.0	54.9,59.1		57.3	55.8,58.8	57.3	54.5,60.0		57.5	56.0,58.9	56.0	52.6,59.4		58.2	56.7,59.6	52.5	49.2,55.[illegible]
Installing an app on your phone that tracks your location and sends push notifications if you might have been exposed to COVID-19					0.65					0.08					0.55				
Extremely/Very	23.9	22.5,25.4	24.4	22.7,26.3		23.8	22.5,25.1	25.1	22.8,27.5		23.9	22.7,25.2	25.2	22.3,28.3		23.6	22.4,24.9	26.7	23.9,29.[illegible]
Moderately	20.2	18.9,21.7	19.3	17.7,20.9		19.4	18.2,20.6	21.5	19.3,24.0		20.1	18.9,21.2	18.6	16.1,21.5		19.2	18.1,20.4	23.4	20.6,26.[illegible]
Not likely	55.9	54.2,57.6	56.3	54.2,58.3		56.9	55.4,58.3	53.4	50.6,56.1		56.0	54.6,57.4	56.1	52.7,59.5		57.2	55.7,58.6	49.9	46.6,53.[illegible]
Using a website to log your symptoms and location and get recommendations about COVID-19					0.45					0.32					0.91				
Extremely/Very	20.6	19.3,22.0	22.0	20.3,23.8		21.6	20.4,22.9	19.6	17.6,21.8		21.2	20.0,22.4	20.9	18.2,23.8		20.9	19.7,22.1	22.5	19.9,25.[illegible]

Moderately	23.5	22.0,25.0	23.5	21.8,25.3	23.3	22.0,24.7	24.1	21.8,26.6	23.4	22.2,24.7	24.1	21.2,27.2	22.9	21.6,24.1	26.9	24.1,30.
Not likely	55.9	54.2,57.6	54.5	52.4,56.6	55.1	53.6,56.6	56.2	53.5,58.9	55.4	54.0,56.9	55.0	51.6,58.4	56.3	54.8,57.7	50.5	47.2,53.

Abbreviations: P - Chi-square p-value; CI - Confidence Intervals
*Cardiometabolic: diabetes, high blood pressure, heart disease, liver disease/end-stage liver disease
†Respiratory: Asthma, chronic lung disease/COPD, bronchitis/emphysema
‡Immune: Cystic fibrosis, cancer, a compromised immune system
§Mental Health: a mental health condition

Multinomial Logistic Regression Results of Attitudes towards COVID-19 mHealth Use across Chronic Health Conditions

Figure 1 displays the multivariable results for the multinomial logistic regression models for each COVID-19 mHealth outcome by chronic health condition, adjusted for age, gender, race/ethnicity, education, income, and residence. The point estimates are available in Supplementary Table 1. Compared to adults without a history of cardiometabolic diseases, adults with cardiometabolic conditions were moderately likely to report the use of a website to log their COVID-19 symptoms (cOR = 1.18, 95% CI 1.02 to 1.36). Compared to adults without a history of respiratory conditions, adults with respiratory diseases were moderately likely to report download and use of an app to track location and potential COVID-19 exposure (cOR = 1.23, 95% CI 1.04 to 1.45). Compared to adults without immune-related conditions, adults with a history of immune-related diseases were moderately likely to report potential download and use of an app to track COVID-19 symptoms and provide health recommendations about COVID-19 (cOR = 1.23, 95% CI 1.01 to 1.49).

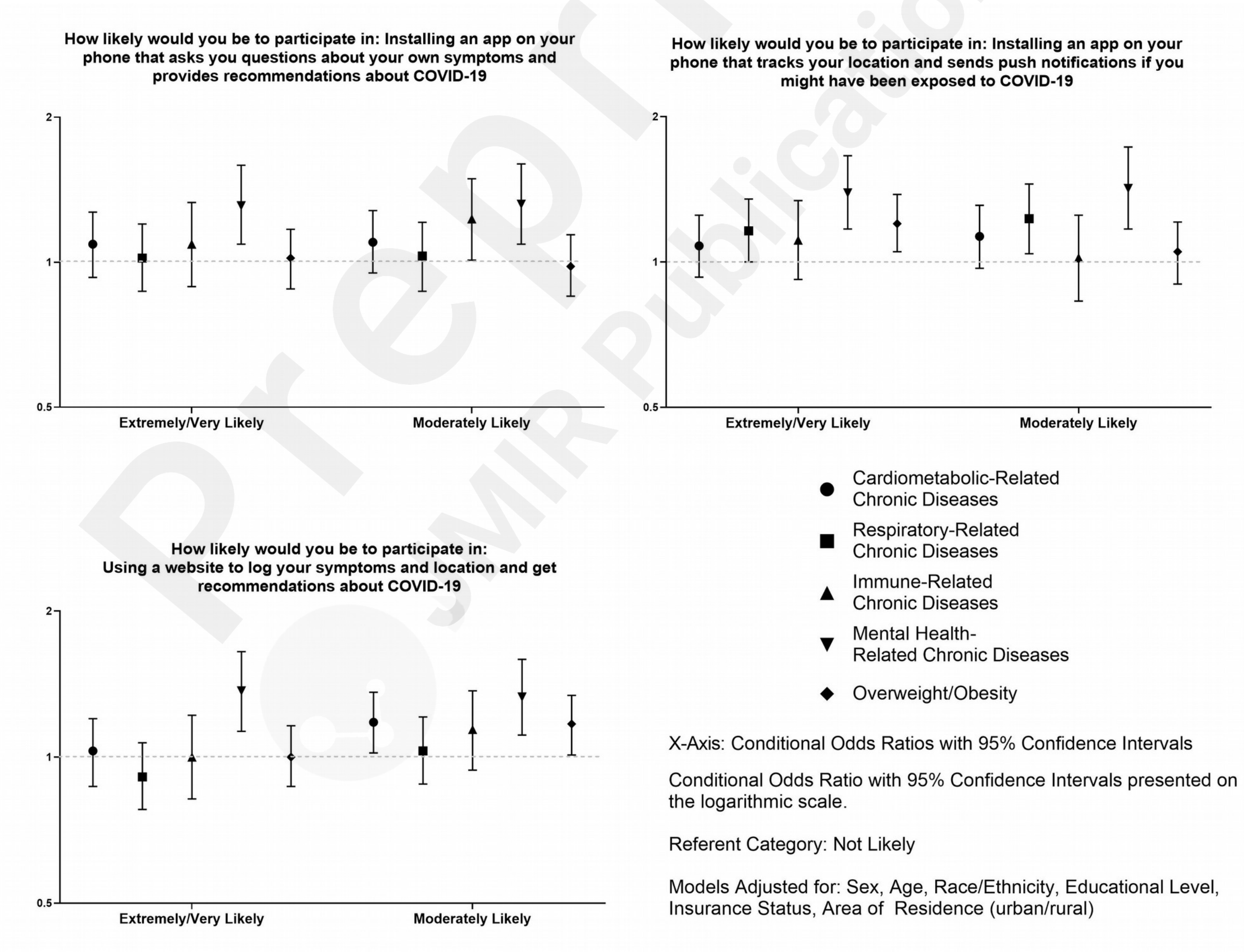

Figure Title: Associations of mHealth Intervention Acceptability with Chronic Disease Group.

Compared to adults without a history of mental health conditions, adults with a mental health history were extremely likely and moderately likely to report potential download and use of an app to track COVID-19 symptoms and provide health recommendations about COVID-19 (cOR = 1.31, 95% CI 1.09 to 1.59 and cOR = 1.32, 95% CI 1.09 to 1.60 respectively). Adults with a mental health history were extremely likely and moderately likely to report download and use of an app to track location and potential COVID-19 exposure, compared to adults without a history of a mental health condition (cOR = 1.39, 95% CI 1.17 to 1.66 and cOR = 1.42, 95% CI 1.17 to 1.73 respectively). Compared to adults without a history of mental health conditions, adults with a mental health history were extremely likely and moderately likely to report the use of a website to log their COVID-19 symptoms (cOR = 1.37, 95% CI 1.13 to 1.65 and cOR = 1.33, 95% CI 1.11 to 1.59 respectively).

Compared to non-obese participants, adults who reported being obese were extremely likely to report download and use of an app to track location and potential COVID-19 exposure (cOR = 1.20, 95% CI 1.05 to 1.38). Participants who were obese were also moderately likely to report the use of a website to log their COVID-19 symptoms compared to non-obese participants (cOR = 1.17, 95% CI 1.01 to 1.34).

Determinants of Extreme/Very likelihood of mHealth Interventions among US adults

Table 3 summarizes the results of the analysis to identify determinants of each mHealth intervention among US adults. Across each mHealth intervention, there are several common determinants. Women have a higher prevalence of being extremely/very likely to use each mHealth intervention compared to men. When compared to those with a college-degree, adults with a high school degree and some college have a lower prevalence of being extremely/very likely to use each mHealth intervention. Racial/ethnic minorities, including non-Hispanic Black, Hispanic, and non-Hispanic Asian adults, have a higher prevalence of being extremely/very likely to use each mHealth intervention compared to non-Hispanic White adults. Additionally, adults with at least one COVID-19 related symptom had a higher prevalence of being extremely/very likely to report installing and using the mHealth apps.

Table 3: Determinants of being extremely/very likely* to utilize COVID-19 mHealth interventions using data

the COVID-19 Impact Survey, a nationally representative survey of the US (n=10,760) (April-June 2020)

	Installing an app on your phone that asks you questions about your own symptoms and provides recommendations about COVID-19		Installing an app on your phone that tracks your location and sends push notifications if you might have been exposed to COVID-19		Using a website t your symptoms a location and g recommendations COVID-19	
	Adjusted PR	95% CI	Adjusted PR	95% CI	Adjusted PR	95%
Age						
18-29	0.71	0.59 - 0.86	-		0.74	0.61 -
30-44	0.80	0.70 - 0.92			0.90	0.78 -
45-59	1.03	0.90 - 1.17			1.02	0.89 -
60+	Ref.				Ref.	
Sex						
Male	Ref.		Ref.		Ref.	
Female	1.12	1.01-1.24	1.12	1.02 - 1.23	1.11	1.00 -
Education						
No HS Diploma	1.07	0.87-1.33	0.99	0.80 - 1.21	0.92	0.73 -
HS Graduate	0.75	0.65-0.87	0.74	0.64 - 0.85	0.68	0.59 -
Some College	0.80	0.71-0.90	0.79	0.71 - 0.88	0.78	0.70 -
Baccalaureate or Above	Ref.		Ref.		Ref.	
Race/Ethnicity						
White, NH	Ref.		Ref.		Ref.	
Black, NH	1.58	1.36-1.83	1.32	1.14 - 1.53	1.67	1.44 -
Hispanic	1.49	1.29-1.73	1.29	1.13 - 1.47	1.47	1.27 -
Asian, NH	1.84	1.47-2.30	1.73	1.43 - 2.10	1.74	1.39 -
Other, NH	1.18	0.90-1.55	1.07	0.83 - 1.38	1.23	0.94 -
At least One COVID-19 Related Symptom†	1.13	1.02-1.25	1.19	1.08 - 1.31	-	
Having at least one chronic disease‡	-		-		-	
Region						
Northeast	Ref.		-		Ref.	
Midwest	0.84	0.71-0.99			0.76	0.64 -
South	0.97	0.83-1.13			0.85	0.73 -
West	0.83	0.71-0.98			0.79	0.67 -
Employed	0.85	0.76-0.95	0.85	0.77 - 0.94	0.78	0.70 -
Uninsured	-		-		0.90	0.74 -
Household Income						
<$50,000	0.96	0.84-1.10	0.82	0.73 - 0.93	0.86	0.74 -
$50,000-<$100,000	0.91	0.80 - 1.04	0.86	0.76 - 0.97	0.85	0.74 -
≥$100,000	Ref.		Ref.		Ref.	
Population Density						
Rural	0.95	0.78 - 1.17	1.04	0.87 - 1.25	0.98	0.81 -
Suburban	0.98	0.85 - 1.12	0.95	0.83 - 1.08	0.93	0.80 -
Urban	Ref.		Ref.		Ref.	

- = p > 0.10 for all categories of the variable in unadjusted analyses

Abbreviations: PR - Prevalence Ratios; CI - Confidence Intervals; Ref - Referent Group

*Respondents were asked if they were: Extremely, Very, Moderately, Not too likely, Not likely at all to participate in each m intervention. We categorized those who responded extremely/very likely to participate as exposed (1), and other as unexposed ((

†Symptoms include: Fever, chills, runny or stuffy nose, chest congestion, skin rash, cough, sore throat, sneezing, muscle o aches, headaches, fatigue or tiredness, shortness of breath, abdominal discomfort, nausea or vomiting, diarrhea, changed sense of taste or smell, loss of appetite

‡Chronic diseases include: diabetes, high blood pressure, heart disease/heart attack/stroke, asthma, COPD, bronchitis or emphy cystic fibrosis, liver disease, cancer, a compromised immune system, and overweight/obesity

Discussion

Principal Results

This study analyzed differences and associations between attitudes towards COVID-19 mHealth use and various chronic health conditions. Adults with chronic health conditions were more likely to report potential use of COVID-19 apps or websites to monitor potential COVID-19 exposure and symptoms, compared to adults without a history of chronic health conditions. Yet, attitudes towards COVID-19 mHealth tools varied significantly across chronic disease conditions and by modality (app versus website). Our study findings highlight the potential for mHealth tools to improve disease self-management and reduce health disparities among individuals with chronic health conditions.

Our study highlighted disparities in attitudes towards COVID-19 mHealth tools across age, sex, race/ethnicity, education, and region. Consistent with prior studies focused on disparities in mHealth use among the general population, we observed that women in our sample were more likely to report positive attitudes towards using an app or website to track potential COVID-19 exposures or symptoms compared to men.[79,88] Previous studies have documented lower rates of mHealth use among individuals of lower socioeconomic backgrounds [80,89]. In our study, irrespective of the report of chronic health conditions, participants with lower levels of education were less likely to report the use of an app or website for COVID-19 symptom or exposure tracking compared to respondents with a college degree or more; similar patterns were observed by income [90].

Our study also highlighted novel findings of a greater likelihood of COVID-19 mHealth tools among racial and ethnic minorities compared to non-Hispanic White respondents in our entire sample. Hispanic, Asian, and non-Hispanic Black respondents were significantly more likely to report the potential use of mHealth tools for COVID-19 exposure and symptom tracking. These attitudes may represent greater awareness among racial and ethnic minority communities of increased susceptibility to COVID-19 morbidity and mortality.[22,25,91] Also, the use of mHealth tools has been increasing among all racial/ethnic groups over the last decade, indicative of both greater access to mHealth tools across all racial/ethnic groups, as well as the potential for mHealth tools to reduce racial/ethnic disparities in chronic disease management, morbidity, and mortality.

An additional novel finding was observed when examining age-related disparities in COVID-19 mHealth attitudes. Contrary to many prior studies documenting increased mHealth use among younger adults, respondents ages 18-29 reported being less likely to use apps or websites for COVID-19 symptom and exposure tracking compared to participants ages 60 or above. These differences may represent greater awareness regarding the risks of COVID-19 among older adults, as well as potential misperceptions of COVID-19 risk among younger populations [92,93].

We also observed geographic differences in attitudes towards COVID-19 mHealth tools with participants from the Midwest, South, and West reporting less interest in the use of apps or websites for COVID-19 symptom and exposure tracking compared to respondents from the Northeast. These disparities are consistent with prior studies focused on regional differences in the digital divide, as well as studies of COVID-19 preventive behaviors across the United States [94]. Our findings may also reflect geographic differences in perceived susceptibility to COVID-19 at the time the survey was administered, given the disproportionate burden of COVID-19 cases in the Northeast at the onset of the pandemic [95,96].

Our findings are of importance given the accumulating evidence identifying cardiovascular diseases, obesity, and diabetes as risk factors for COVID-19 incidence and mortality. In our previous study analyzing COVID-19 preventive behaviors among U.S. adults, we observed that adults with chronic health conditions significantly more likely to engage in many COVID-19 preventive behaviors such as hand washing, use of a face mask, and maintaining appropriate social distancing in public [5,33]. Use of mHealth tools for COVID-19 education, risk reduction, and symptom monitoring may complement existing prevention strategies [97]. Our findings also highlight potential opportunities for mHealth tools to reduce racial and ethnic and age disparities in COVID-19 exposure and outcomes [98,99].

Lastly, our findings highlight the potential for mHealth tools to reduce chronic disease disparities in management and outcomes beyond the COVID-19 pandemic. While there has been a proliferation of mHealth tools across all chronic health conditions, acceptability and long-term of mHealth tools have varied considerably across chronic conditions [100,101]. Variability in mHealth use across chronic health conditions may be related to both the quality of the content and functionality of mHealth tools, as well as user-related preferences [102–106].

Study Strengths and Limitations

Our results should be interpreted within the context of limitations. First, a history of chronic health conditions was based on self-reported data rather than medical records. There may be potential for recall or misclassification bias of chronic health conditions. Also, while we acknowledge the increasing importance of considering multiple chronic conditions, given the complexity of examining multiple chronic conditions, by both number and combination of type of chronic conditions, the examination of COVID-19 mHealth attitudes among individuals with multiple chronic conditions was beyond the scope of this analysis. Second, attitudes towards potential COVID-19 mHealth use are based on self-report rather than downloads or monitoring patterns of actual mHealth usage. As such, there may be potential for social desirability bias in terms of the report of COVID-19 mHealth attitudes which may not correlate to actual COVID-19 mHealth use.

Despite limitations, our study has notable strengths. First, sampling methods used to obtain a nationally representative sample of the U.S. adult population provides the opportunity for increased generalizability. Findings may be helpful to clinicians and public health officials to guide mHealth messaging around COVID-19 prevention, symptom monitoring, and health recommendations. Additionally, study results are drawn from a population that is diverse across social and demographic characteristics as well as health status. Considering that the COVID-19 pandemic has exacerbated health inequities across social groups and groups with chronic health conditions, public health strategies that consider the utility of mHealth approaches across diverse contexts will have a vital role in reducing COVID-19 disparities.

Conclusions

Our study extends previous research in this field by analyzing attitudes towards various COVID-19 mHealth tools across a nationally representative sample of U.S. adults with and without chronic health conditions. Future directions for research may include an examination of COVID-19 mHealth tools among individuals with multiple chronic conditions, as well as associations between COVID-19 mHealth use and COVID-19 knowledge and preventive-behaviors. Our study results have several implications concerning the development of COVID-19 mHealth tools. As the use of mHealth applications has been found to have an impact on improving health outcomes across a range of chronic health conditions, the development of COVID-19 apps should include a focus on user preferences and consider differences in COVID-19 susceptibility across chronic disease conditions. Combining big-data analytic approaches with qualitative data from individuals living with chronic health conditions may yield additional insights to increase acceptability and promote long-term engagement with COVID-19 apps. Lastly, incorporating opportunities for real-time tracking of potential COVID-19 exposure and symptoms among existing health apps across chronic conditions (e.g. mental health, cardiometabolic conditions, respiratory diseases) may provide additional opportunities to strengthen prevention and early detection efforts among populations that are vulnerable to COVID-19 morbidity and mortality.

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Authors' Contributions MCR, JYI, and AR contributed to the drafting of the manuscript. JYI and DCV contributed to the analysis of the data. MCR, JYI, AR, DCV contributed to the interpretation and discussion of the data and review of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

Abbreviations

App: application
mHealth: mobile health
cOR; conditional odds ratio
CI: confidence interval
US: United States

Supplementary Table 1: Conditional odds ratios to evaluate associations of COVID-19 mHealth attitudes by chronic disease status, estimates for Figure 1

There are some options for testing and tracking people who may have COVID-19 in order to help slow the spread of this virus. If these options were available to you, how likely would you be to participate in them?

	Cardiometabolic-Related			Respiratory-Related			Immune-Related			Mental Health-Related			Overweight/Obesity		
Installing an app on your phone that asks you questions about your own symptoms and provides recommendations about COVID-19															
Extremely/Very Likely	1.09	0.93	1.27	1.02	0.87	1.20	1.09	0.89	1.33	1.31	1.09	1.59	1.02	0.88	1.17
Moderately Likely	1.10	0.95	1.28	1.03	0.87	1.21	1.23	1.01	1.49	1.32	1.09	1.60	0.98	0.85	1.14
Not likely	Ref.			Ref.			Ref.			Ref.			Ref.		
Installing an app on your phone that tracks your location and sends push notifications if you might have been exposed to COVID-19															
Extremely/Very Likely	1.08	0.93	1.25	1.16	1.00	1.35	1.11	0.92	1.34	1.39	1.17	1.66	1.20	1.05	1.38
Moderately Likely	1.13	0.97	1.31	1.23	1.04	1.45	1.02	0.83	1.25	1.42	1.17	1.73	1.05	0.90	1.21
Not likely	Ref.			Ref.			Ref.			Ref.			Ref.		
Using a website to log your symptoms and location and get recommendations about COVID-19															
Extremely/Very Likely	1.03	0.87	1.20	0.91	0.78	1.07	1.00	0.82	1.22	1.37	1.13	1.65	1.00	0.87	1.16
Moderately Likely	1.18	1.02	1.36	1.03	0.88	1.21	1.14	0.94	1.37	1.33	1.11	1.59	1.17	1.01	1.34
Not likely	Ref.			Ref.			Ref.			Ref.			Ref.		

Models adjusted for: sex, age, race/ethnicity, educational level, insurance status, area of residence (urban/rural)

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Supplementary Files

Figures

Associations of COVID-19 mHealth Intervention Acceptability with Chronic Disease Group.