Risk Factors for COVID-19 in College Students Identified by Physical, Mental, and Social Health Reported During the Fall 2020 Semester: An Observational Study Using the Roadmap app and Fitbit Wearable Sensors

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Abstract

Background: The coronavirus disease 2019 (COVID-19) pandemic triggered a seismic shift in education, to online learning. With nearly 20 million students enrolled in colleges across the U.S., the long-simmering mental health crisis in college students was likely further exacerbated by the pandemic.

Objective: This study leveraged mobile health (mHealth) technology and sought to: i) characterize self-reported outcomes of physical, mental, and social health by COVID-19 status; ii) assess physical activity through consumer-grade wearable sensors (Fitbit®); and iii) identify risk factors associated with COVID-19 positivity in a population of college students prior to release of the vaccine.

Methods: Detailed methods were previously published in JMIR Res Protocols (Cislo et al). After completing a baseline assessment (i.e., Time 0 [T0]) of demographics, mental, and social health constructs through the Roadmap 2.0 app, participants were instructed to use the app freely, to wear the Fitbit®, and complete subsequent assessments at T1, T2 and T3, followed by a COVID-19 assessment of history and timing of COVID-19 testing and diagnosis (T4: ~14 days after T3). Continuous measures were described using means (M) and standard deviations (SD), while categorical measures were summarized using frequencies and proportions. Formal comparisons were made based on COVID-19 status. The multivariate model was determined by entering all statistically significant variables (P<.05) in univariable associations at once and then removing one variable at a time by backward selection until the optimal model was obtained.

Results: During the fall 2020 semester, 1,997 participants consented, enrolled, and met criteria for data analyses. There was a high prevalence of anxiety, as assessed by the State Trait Anxiety Index (STAI), with moderate and severe levels in N=465 (24%) and N=970 (49%) students, respectively. Approximately, one-third of students reported having a mental health disorder (N=656, 33%). The average daily steps recorded in this student population was approximately 6500 (M=6474, SD=3371). Neither reported mental health nor step count were significant based on COVID-19 status (P=.52). Our analyses revealed significant associations of COVID-positivity with use of marijuana and alcohol (P =.020 and .046, respectively) and lower belief in public health measures (P=.003). In addition, graduate students were less likely and those with ?20 roommates were more likely to report a COVID-19 diagnosis (P=.009).

Conclusions: Mental health problems were common in this student population. Several factors, including substance use, were associated with risk of COVID-19. These data highlight important areas for further attention, such as prioritizing innovative strategies that address health and well-being, considering the potential long-term effects of COVID-19 on college students. Clinical Trial: ClinicalTrials.gov NCT04766788

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ABSTRACT

Background: The coronavirus disease 2019 (COVID-19) pandemic triggered a seismic shift in education, to online learning. With nearly 20 million students enrolled in colleges across the U.S., the long-simmering mental health crisis in college students was likely further exacerbated by the pandemic.

Objective: This study leveraged mobile health (mHealth) technology and sought to: i) characterize self-reported outcomes of physical, mental, and social health by COVID-19 status; ii) assess physical activity through consumer-grade wearable sensors (Fitbit®); and iii) identify risk factors associated with COVID-19 positivity in a population of college students prior to release of the vaccine.

Methods: Detailed methods were previously published in *JMIR Res Protocols* (Cislo et al). After completing a baseline assessment (i.e., Time 0 [T0]) of demographics, mental, and social health constructs through the Roadmap 2.0 app, participants were instructed to use the app freely, to wear the Fitbit®, and complete subsequent assessments at T1, T2 and T3, followed by a COVID-19 assessment of history and timing of COVID-19 testing and diagnosis (T4: ~14 days after T3). Continuous measures were described using means *(M)* and standard deviations *(SD)*, while categorical measures were summarized using frequencies and proportions. Formal comparisons were made based on COVID-19 status. The multivariate model was determined by entering all statistically significant variables ($P<.05$) in univariable associations at once and then removing one variable at a time by backward selection until the optimal model was obtained.

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Conclusions: Mental health problems were common in this student population. Several factors, including substance use, were associated with risk of COVID-19. These data highlight important areas for further attention, such as prioritizing innovative strategies that address health and well-being, considering the potential long-term effects of COVID-19 on college students.

Trial Registration: ClinicalTrials.gov NCT04766788

Key Words: college students; mental health; well-being; COVID-19; mobile health; wearable sensors; global pandemic

INTRODUCTION

As the SARS-CoV-2 virus spread throughout the U.S. and across the world [1], the pandemic disrupted and transformed education overnight [2]. Reacting to the coronavirus disease 2019 (COVID-19) pandemic and subsequent quarantine and isolation measures [3], academic institutions across the nation adapted to virtual learning due to closures of in-person schooling. The unprecedented changes included significant reduction in access to campus resources (e.g., libraries, computing facilities, group study areas, mental health services, exercise facilities), which upended the education landscape [2,4] and created intense stress across institutions. Several recent studies provide evidence for a high prevalence of mental health problems among college students who experienced virtual education [5-16].

Given the potential profound impact of COVID-19 on the health and well-being of college students, our interdisciplinary team leveraged a positive psychology-based mobile health (mHealth) app, *Roadmap 2.0*, as a resilience-building platform for the student population. The Roadmap platform was initially developed to provide support to patients and their family caregivers in healthcare delivery (e.g., information, education, skills-based training) because of its accessibility and scalability [17-23]. This platform was iteratively enhanced to support the health and well-being of the user and to aggregate their raw step and sleep counts, which were collected through the Fitbit® [24].

Herein, this Roadmap platform was leveraged to: i) characterize self-reported outcomes of physical, mental, and social health by COVID-19 status during the fall 2020 semester; ii) assess physical activity through consumer-grade wearable sensors (Fitbit®) by COVID-19 status [25]; and iii) evaluate potential risk factors associated with COVID-19 positivity, including student demographics (e.g., gender, race/ethnicity), substance use, and physical, mental, and social health constructs [25]. This work is important because it may inform future mHealth design interventions for this population. Moreover, these data may be important factors to consider when developing future public health responses that include massive disruptions to mitigate spread of communicable diseases, particularly in emerging, young adults. By using the Roadmap platform, we sought to focus our findings on the nexus between mental and social health constructs with physical activity and COVID-19 status.

METHODS

Study Site

The data coordinating site was a Midwestern academic institution (University of Michigan [U-M], Ann Arbor, MI). Ethical approval for this study was obtained by the U-M Medical School Institutional Review Board (IRBMED), and the study was registered on ClinicalTrials.gov (NCT04766788). All study activities were conducted remotely with no in-person contact, and all study materials were mailed to participants' residences through a U.S. shipping company.

Study Design, Recruitment, and Informed Consent

The Research Protocol has been previously published with more details [25]. Briefly, eligibility for study participation included: age ≥18 years; confirmed undergraduate or graduate U-M student (e.g., on-campus or at home); able to provide digital informed consent; comfortable with reading and speaking English; having access to necessary resources for participating in an mHealth technology-based intervention (i.e., smartphone/tablet and internet access), while also being willing to use personal equipment/internet for the study.

The recruitment period was between September 2020–December 2020. While paper flyers and postings were distributed throughout the campus buildings, the primary mode of recruitment was by the "Targeted Email and Data Service," coordinated by the U-M Registrar's Office, with IRBMED-approval (Figure 1): Consolidated Standards of Reporting Trials [26] Diagram of Participant Flow).

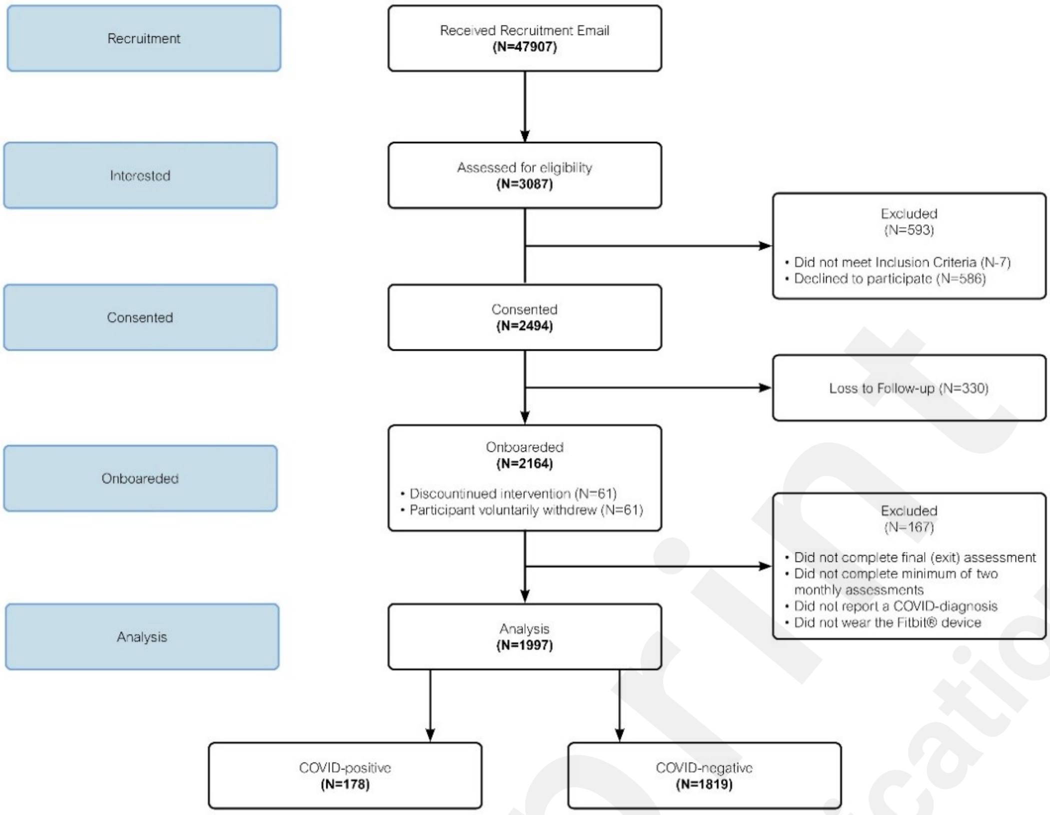

Figure 1: CONSORT Flow Diagram of Participant Recruitment and Enrollment. All current students received the recruitment email. Of those students N=3087 expressed interest and were assessed for eligibility. All eligible students were then sent a consent and N=2494 students signed the consent. Those students were asked for an address to ship the study supplies and were provided the onboarding materials, N=2164 people completed this onboarding. The analysis contained N=1997 students; participants were removed for not providing any Fitbit® data and for not reporting their COVID-19 status (i.e., did not take the T4 survey and at least 2 of the 3 [T1, T2, T3] monthly surveys).

Interested participants who contacted the study team by phone or email received additional study information (e.g., overview of study procedures, risks, benefits). Following confirmation of university student status, the research coordinator emailed the informed consent through the SignNow platform, and the participant signed the document electronically [27].

Study Procedures

The study procedures are outlined in Multimedia Appendix 1.

Wearable Device:

The Fitbit® was mailed to the participants' homes. They were instructed to use it continuously (at least ~40 hours (H)/week) to measure their physical activity, heart rate, and sleep during the monitoring period. The Fitbit® automatically generated accelerometer-based summary data (per proprietary algorithms) that were based on “activity counts” collected over the course of the day. We assessed participant compliance in wearing the Fitbit® by identifying when heart rate data were present through the Roadmap platform using the Fitbit® API [28]. We measured daily wear time using heart rate data with a minutes-level resolution. Compliance was expressed both in hours (0H–24H) and in percentages (i.e., by dividing the hours spent wearing the device by 24H) [29]. Using this assessment of compliance, we calculated the average daily step count for participants who wore the Fitbit® more than 6H between 8AM and 8PM. We chose a cut-off of 6H because the distribution of average daily step count did not change significantly for higher cut-offs. No compliance cut-off was applied for the calculation of asleep hours because the daily average changed by only about .05H between a cut-off of 0H and a cut-off of 11H between 8PM and 8AM.

Roadmap and Fitbit® Apps:

Participants were instructed to download the Roadmap 2.0 (Multimedia Appendix 2) and Fitbit® apps on their smartphone device (both free of charge and publicly available via Apple and Google app stores).

Self-Reported Outcomes:

All self-reported physical, mental, and social health data were collected using Roadmap 2.0, which utilized Qualtrics (Qualtrics, Provo, UT), an online research tool that enables researchers to create study-specific websites for administering study surveys and storing participant data. The data were associated via a unique study participant ID and did not contain any identifying information. Data were stored in the cloud and regularly downloaded and saved on HIPAA-compliant and password-protected university servers. Participants were instructed to complete surveys at baseline (pre-intervention (T0), monthly (T1, T2, T3, and at the study exit (T4) using the Roadmap platform. A list of the survey questionnaires is provided in the Research Protocol [25]. Psychometric properties of these measures are provided in Multimedia Appendix 3. Of note, only the pre-intervention (T0) mental health and health behaviors data were analyzed in the current manuscript. The PHQ-9 (depression) and GAD-7 (anxiety) scales were added into the study protocol after the study began and only a subset of participants answered these items.

Statistical Analyses

For the descriptive statistics, continuous measures were described using mean (M) and standard deviation (SD), while categorical measures were summarized using frequencies and proportions. These data were analyzed using SAS software (SAS Institute Inc., Cary, NC, USA). Formal comparisons were made based on COVID-19 status (e.g., positive, negative) with alpha levels (statistical significance) set at $P<.05$.

Logistic regression models were fit in two stages. First, univariate associations of student demographics and characteristics, mental health, self-reported substance use and social health measures were assessed by COVID-19 status. Second, the multivariate associations of student demographics and characteristics, mental health, self-reported substance use and social health measures were assessed by COVID-19 status. The multivariate model was determined by entering all statistically significant variables ($P<.05$) in univariable associations at once and then removing one variable at a time by backward selection until the optimal model was obtained (i.e., the deviance of the model was minimized).

Next, to test the performance of the multivariate regression model, several receiver operating characteristic (ROC) curves were plotted for candidate models: Model 1 included only demographic variables; Model 2 included demographic and mental health measures; Model 3 included demographic, mental health measures, and self-reported substance use; and Model 4 (Full Model) included all the variables in Models 1 through 3 plus all other significant characteristics and social health variables from univariate associations; as well as Model 5 (Final Model), which was selected by backward stepwise regression from Model 4. Model 5 provided the minimal Akaike Information Criterion (AIC). The Area Under the ROC curve (AUC) represented the prediction accuracy of the current model. When we constructed our models, we observed an increase in accuracy as more variables were added from Model 1 to Model 4. Importantly, even though Model 5 included fewer variables than the Model 4, we did not observe a significant loss in prediction accuracy. Thus, Model 5 was selected as the final multivariate model due to its simplicity. The univariate and multivariate logistic regression were analyzed using R (version 4.1.1). Figures and graphs were generated with GraphPad Prism (version 9.1.0 for Windows, GraphPad Software, San Diego, CA, USA).

RESULTS

Participant demographics by COVID-status

The majority of students consented and enrolled in the study during the months of October and November 2020 (Multimedia Appendix 4), which coincided with the peak number of confirmed cases of COVID-19 at the local, state, and national levels (Multimedia Appendix 5). As shown in Table 1, the student population (total N=1997) consisted of undergraduate (N=1312, 66%) and graduate students (N=670, 34%). The majority of the respondents were female (N=1367, 68%) and White (N=1150, 58%), followed by Asian (N=597, 30%), 2 or more races (N=107, 5%), and Black (N=85, 4%). Ten percent reported their ethnicity as Hispanic/Latinx, and 8% were international students. Approximately one-quarter of the participants were first-generation college students.

Table 1. Participant demographics and characteristics by COVID-19 status

Demographics	Population N (%)	COVID- N (%)	COVID+ N (%)	P
School Year				
Freshman	231 (11.6)	209 (90.5)	22 (9.5)	
Sophomore	355 (17.8)	308 (86.8)	47 (13.2)	
Junior	338 (16.9)	299 (88.5)	39 (11.5)	
Senior	388 (19.9)	357 (92.0)	31 (8.0)	
First Year Graduate	238 (11.9)	218 (91.6)	20 (8.4)	
Second year or greater Graduate	432 (21.6)	413 (95.6)	19 (4.4)	<.001
Gender				
Female	1367 (68.5)	1244 (91.0)	123 (9.0)	
Male	613 (30.7)	559 (91.2)	51 (8.8)	
Other	16 (.8)	15 (93.7)	1 (6.3)	.923
Race				
White	1150 (58.1)	1016 (88.4)	124 (11.6)	
Black or African American	85 (4.3)	80 (94.1)	5 (5.9)	
AIAN	4 (.2)	3 (75.0)	1 (25.0)	
Asian	597 (30.2)	570 (95.5)	27 (4.5)	

Multiracial	107 (5.4)	102 (95.3)	5 (4.7))	
Other	37 (1.9)	32 (86.5)	5 (13.5)	<.001
Ethnicity				
Hispanic or Latino	193 (9.7)	170 (88.1)	23 (11.9)	
Non-Hispanic or Latino	1800 (90.3)	1645 (91.4)	155 (8.6)	.126
Domestic or International				
Domestic	1843 (92.4)	1670 (90.6)	173 (9.4)	
International	151 (7.6)	146 (96.7)	5 (3.3)	.012
First or Continuing Generation				
First Generation	503 (25.3)	461 (91.7)	42 (8.3)	
Continuing Generation	1489 (74.7)	1353 (90.9)	136 (9.1)	.594

[a]Bolded *P*-values indicates significance at *P*<.05, *P*-values are representative of a chi-squared test on the entire demographic.

In this population, N=178 (8.9%) students reported a COVID-19 positive diagnosis (COVID-19 positivity) occurring either before or during the study period (i.e., reported at the baseline, monthly, or exit survey). These individuals were more likely to be non-Asian, non-Multiracial, domestic undergraduate students, living with ≥20 housemates, or owning iPhone smartphones.

The most common COVID-19 symptoms reported by students included body aches (N=93, 51%), loss of smell (anosmia; N=68, 37%), chills (N=67, 36.8%), and cough (N=64, 35%). Additionally, the most common clusters of associated dyadic symptoms were chills and body aches (Cluster 1: N=59) and loss of taste (ageusia) and anosmia (Cluster 2: N=49). The most common triad of symptoms were fever, chills, and body aches (Cluster 3: N=40). Not surprisingly, all respiratory symptoms (e.g., cough, shortness of breath, sore throat) were associated with each other (Figure 2). However, N=53 participants (30% of the N=178 COVID-19 positive) reported that they were asymptomatic.

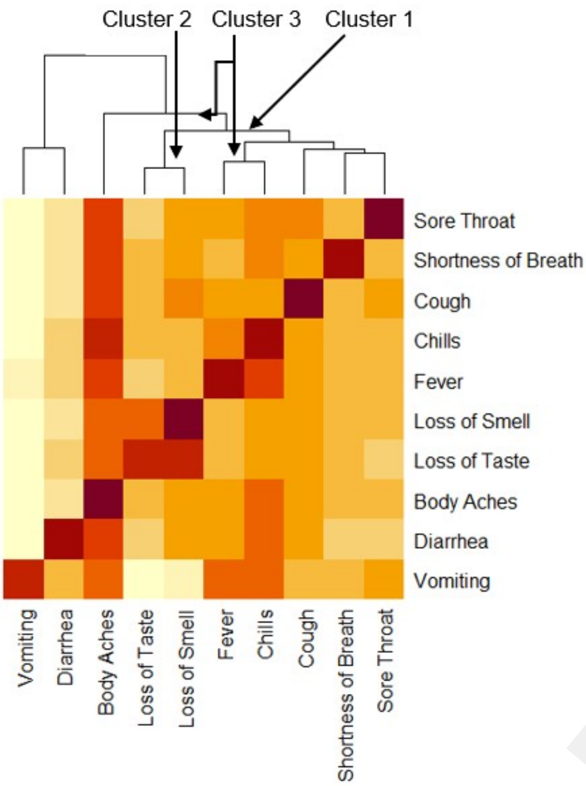

Figure 2: COVID-19 Symptoms. The most common clusters of associated symptoms for dyads were i) chills and body aches (Cluster 1: N=59) and ii) loss of taste (ageusia) and anosmia (Cluster 2: N=49). The most common triad of symptoms was iii) fever, chills, and body aches (Cluster 3: N=40). Body chills occured most frequently and therefore occurs concurrently often. Not surprisingly, all respiratory symptoms (e.g., cough, shortness of breath, and sore throat) were associated with each other.

Self-reported mental and social health by COVID-status

A high prevalence of anxiety, as assessed by the State Trait Anxiety Index (STAI), was reported in this population with moderate and severe levels in N=465 (24%) and N=970 (49%) students, respectively (Table 2). These findings were consistent with self-reported anxiety (N=570, 28%), *depression* (N=373, 19%), or indication of *any mental health disorder* (N=656, 33%) when asked the question "*do you have any of the following health conditions*?" However, there were no differences in these parameters based on COVID-19 status. Similarly, there were no differences in levels of coping, compassion, or flourishing between the groups based on COVID-19 status. Not surprisingly, this population reported high levels (*M*=6.14, *SD*=.88, maximum 7.0) of desire for academic success. Interestingly, lower levels of loneliness and higher social fitness were associated with COVID-19 positivity (Table 2).

Table 2. Self-Report mental health outcomes by COVID-19 status

Mental Health	Population Mean + SD	COVID- Mean + SD	COVID+ Mean + SD	P
STAI Trait	44.49 ± 10.61	44.55 ± 10.60	43.86 ± 10.78	.4062
Compassion	3.46 ± .91	3.46 ± .92	3.46 ± .87	.948
Flourishing	7.35 ± 1.47	7.34 ± 1.46	7.51 ± 1.54	.1362
Loneliness	1.94 ± .58	1.95 ± .58	1.83 ± .61	<.001
Social Fit	5.03 ± 1.14	5.00 ± 1.13	5.29 ± 1.13	<.001
Academic Success	6.14 ± .88	6.13 ± .87	6.21 ± .95	.2851

[a]Bolded *P*-values indicates significance at *P*< .05.

Given the high prevalence of anxiety in our population, we were interested in examining their coping levels. Table 3 details mean scores of the Brief COPE based on problem-focused, emotion-focused, and avoidant coping subscales [30]. As a population, students had the highest mean scores for acceptance, followed by self-distraction, and the lowest mean scores for denial and substance use. Low levels of planning and higher use of humor and substance use were associated with COVID-19 positivity (Table 3). Pearson's *r* correlations revealed a significant, negative association between anxiety and compassion (*r*=-.22) as well as anxiety and flourishing (*r*=-.71). There was also a significant positive correlation between compassion and flourishing (*r*=.22). There was no relationship between compassion and adherence to public health COVID-19 measures (*r*=-.001; Multimedia Appendix 6).

Table 3. Brief COPE outcomes by COVID-19 status

Coping Mechanisms	Population Mean + SD	COVID- Mean + SD	COVID+ Mean + SD	P
Problem-Focused Coping	2.46 ± .59	2.47 ± .59	2.40 ± .57	.139
Active Coping	2.45 ± .76	2.45 ± .76	2.37 ± .72	.158
Instrumental Support	2.39 ± .86	2.40 ± .86	2.34 ± .83	.376
Positive Re-framing	2.48 ± .83	2.47 ± .83	2.54 ± .82	.304
Planning	2.53 ± .80	2.55 ± .80	2.36 ± .80	<.001
Emotion-focused Coping	2.34 ± .42	2.34 ± .42	2.34 ± .40	.923
Emotional Support	2.64 ± .88	2.64 ± .89	2.60 ± .86	.589
Venting	2.14 ± .72	2.14 ± .73	2.13 ± .69	.789
Humor	2.29 ± .92	2.28 ± .92	2.44 ± .86	.020
Acceptance	3.22 ± .68	3.23 ± .67	3.17 ± .67	.208
Self-blame	2.04 ± .81	2.04 ± .81	2.07 ± .85	.751
Religion	1.67 ± .89	1.67 ± .90	1.63 ± .83	.506
Avoidant Coping	1.77 ± .38	1.76 ± .38	1.84 ± .41	.008
Self-distraction	2.96 ± .72	2.95 ± .72	2.99 ± .70	.485

Denial	1.20 ± .44	1.20 ± .43	1.26 ± .48	.096
Substance Use	1.40 ± .69	1.38 ± .66	1.62 ± .84	<.001
Behavioral Disengagement	1.53 ± .65	1.53 ± .64	1.49 ± .68	.472

[a]Bolded *P*-values indicates significance at *P*<.05.

Self-reported substance use by COVID-status

Among all students, cigarette smoking was low (N=23, 1.2%), while those who reported any marijuana use, vaping, and alcohol use were N=847 (42.6%), 431 (21.6%), and 1,600 (80.4%), respectively, which were all associated with COVID-19 positivity (Table 4). Moreover, students who reported a mental health problem were significantly more likely to use marijuana (odds ratio [OR]=1.76; 95% confidence interval [CI]: 1.46, 2.13), consume alcohol (OR=2.22, 95% CI: 1.70, 2.90), engage in vaping (OR=1.64; 95% CI=1.32, 2.04), or smoke cigarettes (OR=4.76, 95% CI: 1.95, 11.63; Multimedia Appendix 9).

Table 4. Health behaviors including substance use and exercise by COVID-19 status

Health Behaviors	Population N (%)	COVID- N (%)	COVID+ N (%)	P
Marijuana				
Yes	847 (42.6)	737 (87.0)	110 (13.0)	
No	1143 (57.4)	1076 (94.1)	67 (5.9)	<.0001
Smoking				
Yes	23 (1.2)	20 (87.0)	3 (13.0)	
No	1973 (98.8)	1798 (91.1)	175 (8.9)	.485
Vaping				
Yes	431 (21.6)	359 (83.3)	72 (16.7)	
No	1563 (78.4)	1458 (93.3)	105 (6.7)	<.001
Alcohol Consumption				
Yes	1600 (80.4)	1435 (89.7)	165 (10.3)	
No	391 (19.6)	379 (20.9)	12 (3.1)	<.001
Exercise				
Yes	1917 (96.0)	1745 (91.0)	172 (9.0)	
No	79 (4.0)	74 (93.7)	5 (6.3)	.418

[a]Bolded p-values indicates significance at *P*<.05.

Using Fitbit® data to assess physical health in college students by COVID-status

In addition to completing longitudinal survey measures, students also provided continuous physiological data by wearing the Fitbit® device throughout the study period. The average wear time of the device was: 14.5H (of the 24H day), 7.4H during daytime (between 8AM–8PM), and 7.1H during nighttime (between 8PM-8AM). As shown in Figure 3, we observed a modest decline in compliance over the 90 days of the study, from an average of 16.1H for the first 30 days, to 13.5H for the last 30 days. Students who reported COVID-19 positivity had significantly lower average daily compliance (24H) than students who did not (*P*=.04). Multimedia Appendix 7 shows the distribution of average daily compliance by COVID-19 status. The average daily steps in this student population were approximately 6500 (*M*=6474, *SD*=3371; Multimedia Appendix 8). There were no significant differences in average daily step counts based on COVID-19 status (*P*=.52).

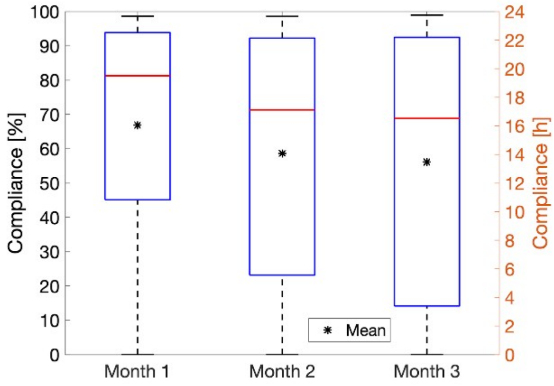

Figure 3: Fitbit® Compliance Over Time – Each boxplot represents the daily compliance averaged chronologically for each 30-day of the 90-day study period for all participants.

Multivariate Risk factors for COVID-positivity

In the final multivariate model of student demographics and characteristics, including physical, mental, and social health variables, individuals who reported marijuana or alcohol use and lived with a greater number of housemates (≥20) were at increased risk of developing COVID-19 positivity. However, being a graduate student as well as being an individual who aligned with public health measures were associated with COVID-19 negativity (Table 5). Graduate students' protection from COVID-19 may have been due to their less dense living environments compared with undergraduate students (*P*<.001). Model 5 with an AUC of 85% is available in Multimedia Appendix 10. All models that were significant at the univariate level and included in the multivariate model are shown in Multimedia Appendix 11.

Table 5. The final multivariate model

Predictor	Estimate	Std Error	P value

	(Intercept)	-1.9116	1.0022	.0565	Demographic
Race	Black or African American	.0170	.5414	.9749	
	AIAN	1.5975	1.2206	.1906	
	Asian	-.4895	.2723	.0722	
	Multiracial	.9844	.5664	.0822	
	Other	-1.1114	.6125	.0696	
Grade	Sophomore	.0873	.3488	.8023	
	Junior	-.0834	.3512	.8122	
	Senior	-.5921	.3686	.1082	
	Grad Student- 1st Year	-.9850	.4520	.0293	
	Grad Student- 2nd Year	-1.1648	.4160	.0051	
	Other	-14.1032	596.5290	.9811	
Coping: Planning	Planning	-.2215	.1269	.0809	Mental
Marijuana	Binary Usage	.5523	.2387	.0207	Substance use
Alcohol	Binary Usage	.7483	.3756	.0464	
Vaping	Binary Usage	.3807	.2342	.1040	
Student social fit	Numeric	.1774	.0988	.0726	Other
Public Health Belief	Numeric	-.2219	.0752	.0032	
Loneliness	Numeric	-.3217	.1902	.0908	
Belief in COVID likeliness	Somewhat agree	.1460	.5055	.7727	
	Neither agree nor disagree	.3415	.4947	.4900	
	Somewhat disagree	.5355	.4869	.2714	
	Strongly disagree	.7695	.5485	.1607	
	Already Had COVID	6.7463	.8943	**<.001**	
Number of Housemates	1-3	-.1159	.2905	.6900	
	3-10	-.4007	.3362	.2333	
	10-20	.6635	.5937	.2638	
	20+	1.3433	.5160	**.0092**	

[a]Bolded *P*-values indicates significance at *P*<.05.

DISCUSSION

Principal Results

A major finding in the current paper points to concerns of adverse mental health symptoms reported by college students, confirming data from other recent studies [31-34]. When looking at the STAI trait, 73% of our study population had moderate or severe anxiety. Our study also used the GAD-7 and PHQ-9 assessments of anxiety and depression, respectively, in a subset of our students. In data not shown, we found that approximately 52% (in those who completed the GAD-7, N=1366) reported anxiety and 65% (in those who completed the PHQ-9, N=1365) reported depressive symptoms. These data further highlight the high prevalence of mental health problems in today's college students [35]. Indeed, the upsurge in college student mental health problems has escalated to alarming levels nationally [32,34,36], likely amplified by the effects of the global pandemic [2,15].

Our study did not find a difference in mental health data reported by COVID-19 status, whereas substance use was significantly associated with COVID-19 positivity. It is possible that in some students who reported mental health problems, their coping strategies may have included substance use behaviors (e.g., marijuana, alcohol consumption), which tend to be social activities occurring in groups (i.e., more than one individual). Indirectly, this may have accounted for increased COVID-19 risk due to less vigilant safety practices. Alternatively, in other students who reported mental health problems, they may be associated with (or due to) isolation, thereby decreasing their COVID-19 risk. It is possible this competing process canceled out any significant total effect of mental health problems by COVID-19 status.

Comparison with Prior Work

This study leveraged mHealth technology to characterize the demographics and physical, mental, and social health of college students during a global pandemic. During a unique period in history where all in-person research activities were halted, the mHealth platform facilitated this type of data collection. The findings herein were self-reported by students prior to the availability of nationwide COVID-19 vaccines. Approximately 9% of students who participated in this study reported COVID-19 positivity. Across the nation, there were over 30 million cumulative reported positive COVID-19 cases by April 01, 2021 [37], which was approximately 9.2% of the U.S. population. In the state of Michigan, where this study was conducted, ~750,000 COVID-19 cases occurred by this time (~7.5% of the population). In addition, cases in Michigan have been most prevalent in the 20-29 age group [38], which may be due to students living in close proximity during the pandemic.

In our college sample, the most common symptoms were body aches, anosmia, chills, and cough. Interestingly, in a large meta-analysis of 9 countries and 24,410 adults, the most common reported symptoms were fevers (78%) and cough (58%) [39]. However, many of the studies contributing to this meta-analysis were in patients requiring hospitalization, which suggests that these symptoms may have been more common in infections with severe clinical phenotypes. Another recent study used an mHealth app that reported symptomology and COVID-19 test results in ~3.2 million users. Within the symptomatic population, 60.4% reported a cough, while only 42.7% reported a fever [40]. Those data were consistent with our findings in that 51.2% of our symptomatic population reported cough and 45.6% reported fever.

We found that second-year graduate students, Asians and Multi-racial students, and international students were significantly less likely to report COVID-19 positivity. There was also an association between an increased number of roommates and an increased risk of COVID-19 positivity. Graduate students in our sample lived with significantly fewer people, presumably decreasing their risk of COVID-19. Marijuana and alcohol consumption were significant risk factors for COVID-19. Additionally, students who agreed/believed in public health measures were less likely to report COVID-19 positivity.

Not surprisingly, we observed a relatively modest decrease in Fitbit® compliance over the study duration. This was likely due to decreased engagement with both the Fitbit® device and the study over time. Despite the ease-of-use of consumer-grade wearable sensors, “wearables abandonment” is a well-documented issue [41]. Nonetheless, we observed a large proportion of highly compliant students (i.e., daily wear time >14H) and a smaller proportion with lower levels of compliance (<2H). Students who reported COVID-19 positivity showed a bimodal-like distribution in their Fitbit® compliance compared with COVID-19 negative students. The NetHealth study recorded overall higher levels of compliance for a longer period using a similar Fitbit® device in a college student population [29]. However, the NetHealth study was conducted from 2015 to 2017 (i.e., prior to COVID-19), which may help explain the different behaviors. Additionally, the differences may be attributed to the compensation model of the studies. The study herein did not incentivize regular data reporting outside of providing the Fitbit® device, whereas the NetHealth study did (i.e., provided monetary compensation for regular Fitbit® use and data reporting).

The average daily step count observed in the current population was *M*=6474 (*SD*=3371), which was a relatively low level of physical activity [42]. The NetHealth study conducted on 692 college students reported an average pre-pandemic daily step count of *M*=11258 (*SD*=5874) [43]. This large difference in physical activity was likely due to pandemic procedures and norms (e.g., isolation, quarantine, public health guidelines). Specifically, during that time the periodic walks to and from classes (on campus) were possibly limited by the virtual learning environment and strict isolation and quarantine guidelines mandated by the university during peak COVID-19 cases (Figure 4). Of note, data analyses are forthcoming in examining the impact of Roadmap's resilience-based activities on physical, mental, and social health outcomes over time (pre-, post-), given the study's longitudinal design. Moreover, we currently have a "Re-contact Student Study" (post-vaccine era) in the same study population who participated in the initial 2020-2021 Student Study, which will allow us to compare data from the pre- and post-vaccine eras in future analyses.

Limitations

We interpret the findings herein within the context of several limitations. Due to the single institution design, our findings are not generalizable outside of our student cohort. In the fall 2020 semester, the undergraduate U-M student population was represented by the following race/ethnicity categories: 17307 (55.2%) White; 5,111 (16.3%) Asians; 2301 International (7.4%); 2,187 (7%) Hispanic/Latinx; 1615 (5.2%) Not Indicated; 1508 (4.8%) 2 or More; 1249 (4%) Black/African American; 36 (.11%) American Indian/Alaska Native; and 14 (.04%) Native Hawaiian/Other Pacific Islander. While our cohort recruited similar proportions of racial/ethnic categories reflective of the U-M student demographics, there was a greater percentage of Asian students. In addition, females were much more likely to participate in our study than males (68% compared with 31%), despite a roughly equal percentage of gender types attending the U-M (50.3% female, 49.7% male).

Secondly, data attrition resulting from wearable abandonment or digital fatigue may have underestimated the student population's physical activity based on their daily step count. Future work involving emerging adults should consider types of compensation models to incentivize engagement [29] as well as study designs that are adaptive rather than one-size-fits-all [44]. Lastly, COVID-19 diagnosis and symptoms were based on self-report. Our study was limited by resources that did not allow for routine surveillance testing during the study period or access to student medical records to confirm COVID-19 diagnosis and symptoms reporting.

Despite these limitations, our study had robust recruitment during a period wherein face-to-face research activities were largely halted, indicating the feasibility and merit of conducting a longitudinal study of this nature during a global pandemic. Mobile health technology enabled the team to conduct a virtual and contactless study from recruitment, informed consent, enrollment, onboarding, and multi-parameter data collection, including self-report measures and physiological data. The study design aligned with student preferences regarding their ease-of-use of technology, such as use of Fitbits® and smartphones.

CONCLUSION

In summary, the findings of the current study provide initial data supporting the use of an mHealth platform during a global pandemic while in-person activities were significantly altered. The most significant factors associated with risk of COVID-19 positivity in this population included student demographics (e.g., graduate student, number of roommates), behavioral factors (e.g., marijuana use, alcohol consumption), and beliefs in public health measures. Soberingly, a substantial proportion of this student population was facing a mental health problem and substance use was common. Over the course of the COVID-19 pandemic, students' educational opportunities have been abruptly disrupted, which may have long-term, unintended consequences. Thus, attention to the current student mental health crisis is imperative with an urgent need to develop novel and timely interventions that address student health and well-being [2].

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Conflicts of Interest
The study team reports that we have no conflicts of interest to declare.

Abbreviations
COVID-19: coronavirus disease 2019
H: hours
IRBMED: U-M Medical School's Institutional Review Board
mHealth: mobile health
U-M: University of Michigan
U.S.: United States

Authors' Contributions
Kristen Gilley: Writing-original draft; study coordination; study recruitment; study consent; study onboarding; data and figure curation

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Miao Yu: Writing-original draft; data and figure curation

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Niyanth Reddy: Writing-review/editing, data curation

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Joel Gagnier: Writing-review/editing; methodology

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Julia Lee Cunningham: Writing-review/editing; survey measurement selection; methodology

Stephen Cain: Writing-review/editing; supervision; methodology

Muneesh Tewari: Data curation, investigation, methodology, resources, supervision, visualization, writing-original draft, writing-review/editing.

Sung Choi: Data curation, investigation, methodology, resources, supervision, visualization, writing-original draft, writing-review/editing, creator of Roadmap 2.0 app.

MULTIMEDIA APPENDICES

Multimedia Appendix 1: Study Procedures. Recruitment occurred in college students that were 18 years or older through a targeted email and posted flyers. Interested participants reached out through email and study coordinators performed an informed consent process. Participants were then onboarded via HIPAA-approved teleconference (e.g., Zoom) or recorded video. Onboarding included downloading the Roadmap 2.0 and Fitbit® apps as well as completing the baseline survey. Participants were instructed to continue Fitbit® syncing and monthly surveys for the next 3 months. Two weeks after the final monthly survey, students took one more closing survey and Fitbit® data were collected to the end of the academic year.

Multimedia Appendix 2: Main Components of the Roadmap App

Multimedia Appendix 3: Psychometric Properties of Self-Report Measures

Multimedia Appendix 4: Student Enrollment over Time

Multimedia Appendix 5: COVID-19 Cases at the Local (University of Michigan and Washtenaw County), State (Michigan) and National (U.S.) Levels

Multimedia Appendix 6: Correlations of flourishing, compassion, STAI Trait, and Public Health Beliefs

Multimedia Appendix 7: Distribution of Compliance by COVID-Status – Distribution of the average daily compliance per participants by COVID-status. The mean and standard deviation of each distribution are given.

Multimedia Appendix 8: Distribution of the average daily step count over the 90-day study period. The mean and standard deviation of each distribution are given.

Multimedia Appendix 9: Odds Ratios of Substance Use where no report of a mental health condition is the reference group compared to those who reported any mental health condition

Multimedia Appendix 10: Model Selection. Model (1) included only demographic variables; Model (2) included demographic and mental measures; Model (3) included demographic, mental measures, and self-reported substance use; and (4) the Full Model included all the variables in models (1) through (3) plus all other significant characteristics and social health variables from univariate associations as well as (5) the Final Model, which was selected by backward stepwise regression from the Full Model (4). The Final Model provided the minimal Akaike information criterion (AIC). The Area Under the ROC curve (AUC) represented the prediction accuracy of the current model. When we constructed our models, we observed an increase in accuracy as more variables were added from Model (1) to Model (4). Importantly, even though the Final Model (5) included fewer variables than the Full Model (4), we did not observe a significant loss in prediction accuracy. Thus, the Final Model (5) was selected as the final multivariate model due to its simplicity.

Multimedia Appendix 11: Univariate significant models

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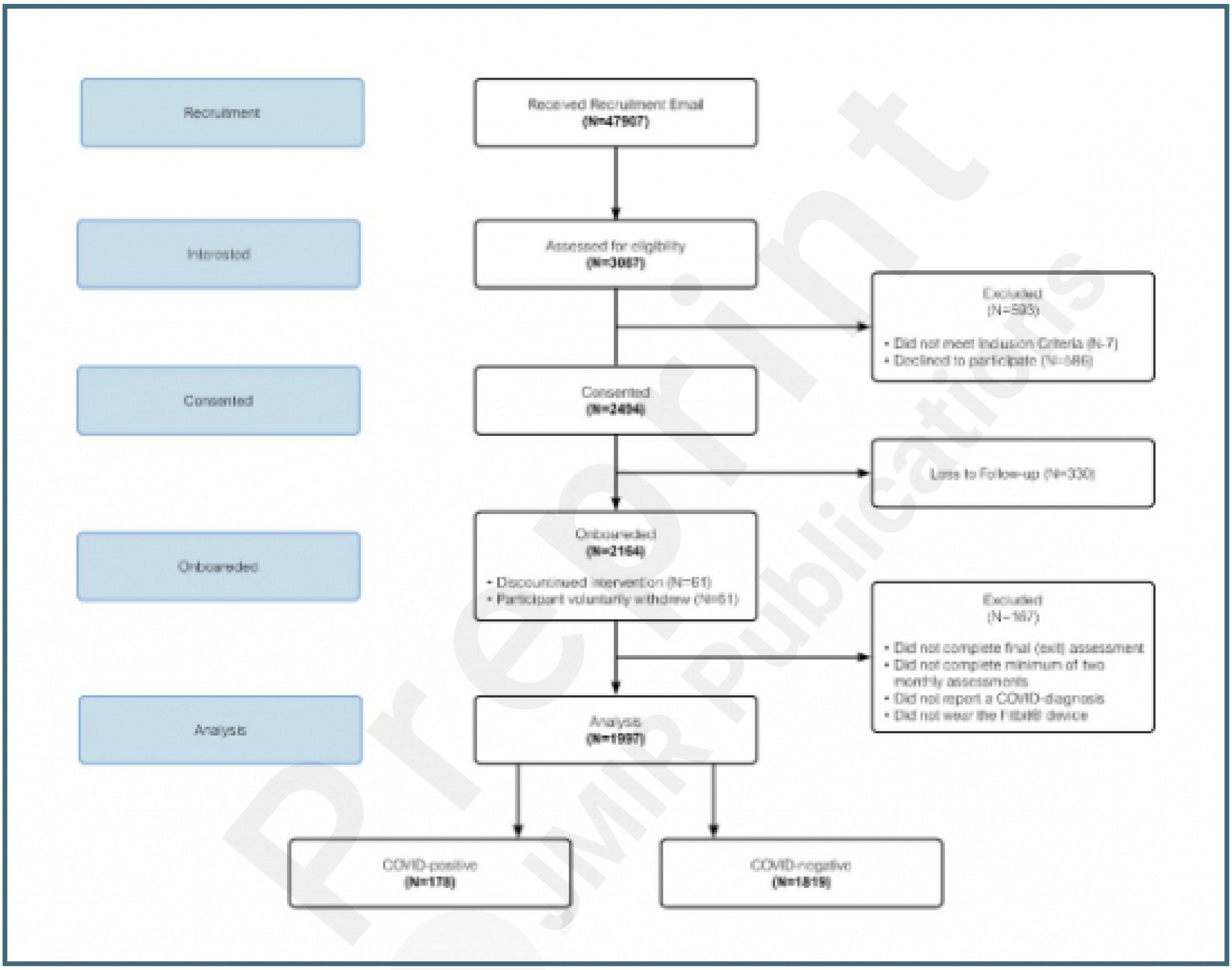
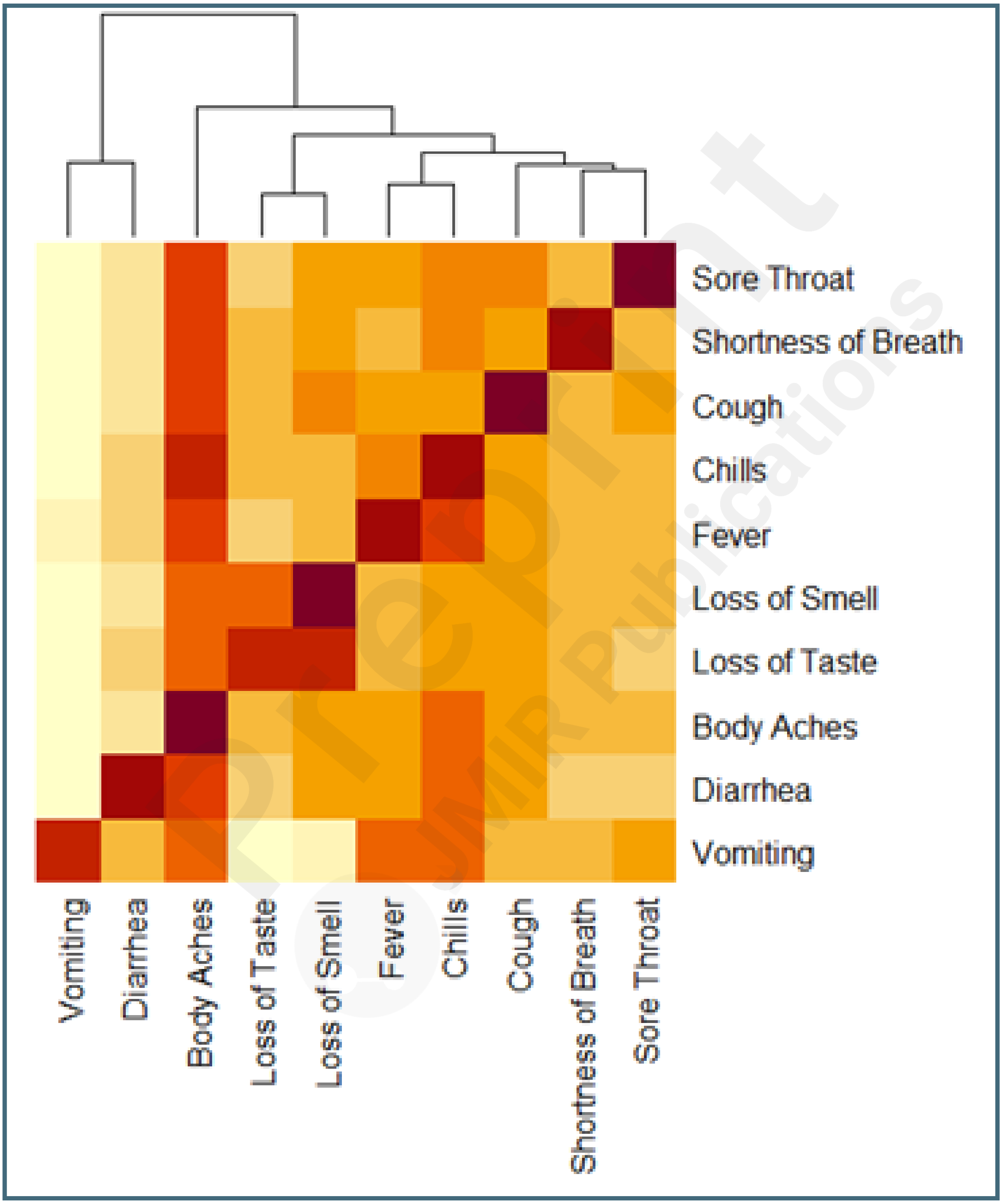
Supplementary Files

Figures

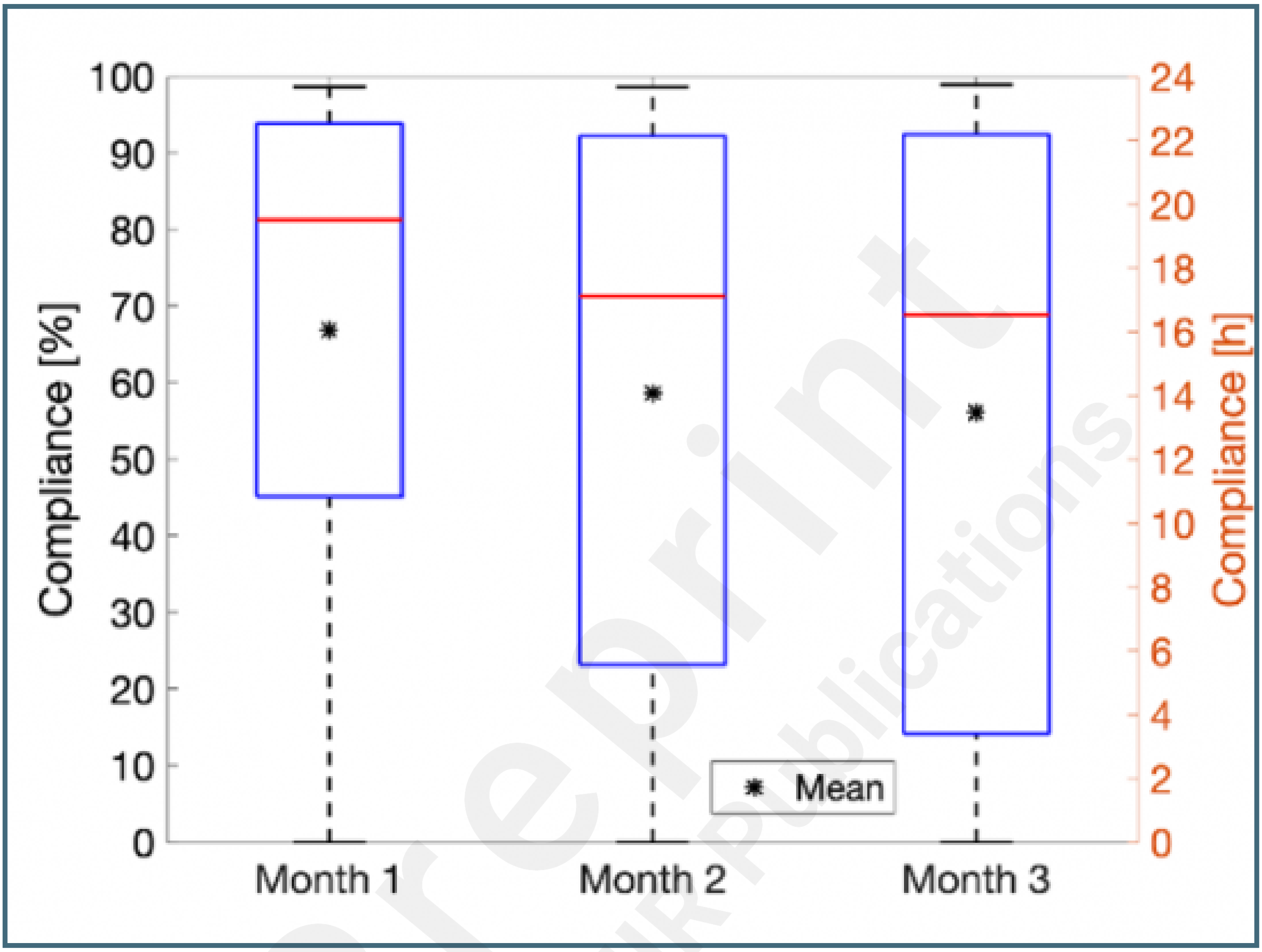
CONSORT Flow diagram of participant recruitment and enrollment. All current students received the recruitment email. Of those students N=3087 expressed interest and were assessed for eligibility. All eligible students were then sent a consent and N=2494 students signed the consent. Those students were asked for an address to ship the study supplies and were provided the onboarding materials, N=2164 people completed this onboarding. The analysis contained N=1997 students; participants were removed for not providing any Fitbit® data and for not reporting their COVID-19 status (i.e., did not take the T4 survey and at least 2 of the 3 [T1, T2, T3] monthly surveys).



COVID-19 Symptoms. The most common clusters of associated symptoms for dyads were i) chills and body aches (Cluster 1: N=59) and ii) loss of taste (ageusia) and anosmia (Cluster 2: N=49). The most common triad of symptoms was iii) fever, chills, and body aches (Cluster 3: N=40). Body chills occured most frequently and therefore occurs concurrently often. Not surprisingly, all respiratory symptoms (e.g., cough, shortness of breath, and sore throat) were associated with each other.



Fitbit® compliance over time – Each boxplot represents the daily compliance averaged chronologically for each 30-day of the 90-day study period for all participants.



Multimedia Appendixes

Study Procedures. Recruitment occurred in college students that were 18 years or older through a targeted email and posted flyers. Interested participants reached out through email and study coordinators performed an informed consent process. Participants were then onboarded via HIPAA-approved teleconference (e.g., Zoom) or recorded video. Onboarding included downloading the Roadmap 2.0 and Fitbit® apps as well as completing the baseline survey. Participants were instructed to continue Fitbit® syncing and monthly surveys for the next 3 months. Two weeks after the final monthly survey, students took one more closing survey and Fitbit® data were collected to the end of the academic year.
URL: http://asset.jmir.pub/assets/234402848bec444abea19d153bc77a51.png

Main components of the roadmap app.
URL: http://asset.jmir.pub/assets/43f970d1fb41036fcfd0e9ef9f461d21.png

Psychometric properties of self-report measures.
URL: http://asset.jmir.pub/assets/af0b801eb650007efaf719b2df71eefb.doc

Student enrollment over time.
URL: http://asset.jmir.pub/assets/2872cfabb3205f6fa3c2e2e15f249dd7.png

COVID-19 Cases at the local (University of Michigan and Washtenaw County), state (Michigan), and national (U.S.) levels. University: UM Covid-19 data. Campus Maize and Blueprint. 2021. https://campusblueprint.umich.edu/dashboard. County and State: Michigan.gov. 2021. Coronavirus. https://www.michigan.gov/coronavirus. United States: Center for Disease Control. 2021. COVID data tracker. https://covid.cdc.gov/covid-data-tracker/#trends_dailytrendscases.
URL: http://asset.jmir.pub/assets/f13ae205e3171a570694fbfc751ad4ae.png

Correlations of flourishing, compassion, STAI trait, and public health beliefs.
URL: http://asset.jmir.pub/assets/b8340025225a208d6a72982009253dad.doc

Distribution of compliance by COVID-Status – Distribution of the average daily compliance per participant by COVID-status. The mean and standard deviation of each distribution are given.
URL: http://asset.jmir.pub/assets/4db6ead8d7402fc9e2d6be636a59b7ab.png

Distribution of the average daily step count over the 90-day study period. The mean and standard deviation of each distribution are given.
URL: http://asset.jmir.pub/assets/656be1b387cde7d20dbd544877516cf9.png

Odds Ratios of substance use where no report of a mental health condition is the reference group compared to those who reported any mental health condition.
URL: http://asset.jmir.pub/assets/5b2d6ee2ec8a270d54f0a1292f7c5713.doc

Model selection. Model (1) included only demographic variables; Model (2) included demographic and mental measures; Model (3) included demographic, mental measures, and self-reported substance use; and (4) the Full Model included all the variables in models (1) through (3) plus all other significant characteristics and social health variables from univariate associations as well as (5) the Final Model, which was selected by backward stepwise regression from the Full Model (4). The Final Model provided the minimal Akaike information criterion (AIC). The Area Under the ROC curve (AUC) represented the prediction accuracy of the current model. When we constructed our models, we observed an increase in accuracy as more variables were added from Model (1) to Model (4). Importantly, even though the Final Model (5) included fewer variables than the Full Model (4), we did not observe a significant loss in prediction accuracy. Thus, the Final Model (5) was selected as the final multivariate model due to its simplicity.
URL: http://asset.jmir.pub/assets/832f1e5ef24e1626f64c301d0541d0ff.png

Univariate significant models.
URL: http://asset.jmir.pub/assets/b59dbfa6a3ad7c7f7f48c6a25f368dfb.doc

TOC/Feature image for homepages

College students using their smartphone apps.