A US population health survey on the impact of COVID-19 using the EQ-5D-5L

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Abstract

Background: In addition to health and economic consequences, the COVID-19 pandemic has likely affected population health-related quality of life (HRQoL).

Objective: To assess the impact of COVID-19 on US population health using the EQ-5D-5L.

Design: We surveyed respondents on health status, employment, and anxiety/depression. We collected information on demographics, brief medical history, socioeconomic status, current COVID-19 status, sleep, dietary, and financial spending changes. Results were compared to US population norms. Predictors of EQ-5D-5L utility were analyzed using post-Lasso OLS regression, a machine learning algorithm designed to enhance prediction accuracy by avoiding overfitting. Robustness of regression coefficients were analyzed with E-Values to quantify unmeasured confounding.

Participants: Amazon MTurk users.

Main Measures: EQ-5D-5L utility score by age group.

Key Results: Survey respondents (n=2776) reported significantly worse mean (SD) HRQoL utility as captured by the EQ-5D-5L among 18-24 year olds, 0.752 (0.281) vs. online, 0.844 (0.184) (p=0.001) and face-to-face norms, 0.919 (0.127) (p<0.001). Among ages 25-34, utility was worse compared to face-to-face norms only (0.825 (0.235) vs. 0.911 (0.111), p<0.001). Among ages 35-64, utility values were higher during-pandemic but only vs. online norms (0.845 (0.195) vs. 0.794 (0.247), p<0.001). At age 65+, utility values (0.827 (0.213)) were similar across all samples. Increasing age and income were correlated with increased utility, while Hawaiian/Pacific islander race, Hispanic ethnicity, married, living alone, history of chronic illness, fear of COVID-19's impact on health, and having a family member diagnosed with COVID-19 were associated with worse utility scores. Results were relatively robust to unmeasured confounding.

Conclusions: HRQoL has decreased during the pandemic compared to US population norms, especially for ages 18-24. The mental

Introduction

The COVID-19 global pandemic has resulted in public panic and worldwide chaos, imposing significant social, economic, and health consequences. The media has reported countless anecdotes of anxiety, depression,[1–4] and domestic violence,[5–7] while scientific journals have published numerous case reports and clinical studies from all over the world.[8–10] As of July 29, 2020, a simple PubMed search of "covid 19 depression" yields 445 articles. With global lockdown policies of varying severities and the cancellations /closures of events, businesses, and entertainment venues, it is abundantly clear that the pandemic has significantly impacted the health status and quality-of-life of individuals around the world, and has especially exacerbated mental health issues, including those of the clinicians and healthcare workers (HCWs), who are responsible for treating mental health issues in the general public.[11,12]

Missing from the COVID-19 literature is a standard method that allows for the quantification of health-related quality-of-life (HRQoL) and thus, comparisons across different disease states and conditions. An example is the EQ-5D-5L, a generic measure of health that is globally used in population health studies and economic evaluations because of its generalizability and ease of administration.[13] It is short, simple, and validated in both online and face-to-face panels in the United States.[14–16] Respondents rate mobility, self-care, usual activities, pain/discomfort, and anxiety/depression on a category of 1-5 indicating no to extreme problems. The responses can be converted into health utility scores by applying a societal preference function which generates scores anchored at 0 for dead, and 1 perfect health, with negative values for states considered worse than dead. Such scores can be used in cost-utility analyses (CUA) to guide health technology assessment. Also included is a Visual Analog Scale (VAS), asking respondents to rate their overall health on a scale of 0-100.[14] The EQ-5D-5L has been widely validated in hundreds of countries and languages, thus providing a standardized approach to measuring and comparing health within and across nations.[14]

The primary objective of this study was to assess the impact of COVID-19 on US population health using the EQ-5D-5L. Our secondary aim was to translate these findings into total lives lost by age group.

Methods

This study used the first wave of a three-wave longitudinal panel to assess changes in HRQoL over time in the US (n=2,776). Amazon's Mechanical Turk (MTurk) platform[17] was used to survey respondents on demographics, COVID-19 status, and behavior and employment changes related to COVID-19 (Supplementary material). Amazon MTurk allows large-scale surveys to be implemented in an online format, and can thus be useful for clinical research.[18,19] Respondents, known as "Workers", can voluntarily complete "Human Intelligence Tasks" (HITs) according to criteria set by the research team ("Requestors"), such as age or sex. MTurk automatically grants a Masters Qualification to Workers based on statistical models that analyze Worker performance based on several Requester-provided and marketplace data points; those who score the highest across these key data points are granted the Masters Qualification.[17]

We surveyed respondents on health (EuroQol EQ-5D-5L and Veterans RAND 12, VR12), employment and productivity (Work Productivity and Impairment Questionnaire, WPAI), and anxiety and depression (Patient Health Questionnaire-4, PHQ4). The survey also consisted of questions on demographics, including brief medical history, socioeconomic status, current COVID-19 status, sleep, dietary, and financial spending changes, and employment status changes. Finally, the survey asked respondents to rate their fear of COVID-19's impact on their health and financial situations on a scale of 0-10, whether respondents were under mandatory social distancing, and respondents' level of support for social distancing policies on a scale of 0-10.

We assessed the quality and demographics of responses throughout the data collection process to refine the phrasing of questions and to ensure a relatively even distribution of sample respondents across age and gender similar to general US population using census data (Table 1). Additional criteria restricting respondents to be those aged 55+ was added after initial 2000 subjects to improve the representativeness of the sample.

Demographics from our sample were compared to the general US population based on US census data. Utility values were calculated from EQ-5D-5L responses using US-derived value weights.[16] We compared EQ-5D-5L results with pre-pandemic results we collected prior to COVID-19 (n=40) and with US population norms from previously derived online (n=2,018) as well as face-to-face (n=1,134) interviews.[15] We used t-tests and chi-squared tests for numeric and categorical variables respectively to identify statistically significant differences. A prior significance was set at 0.05. The EQ-5D-5L domain responses were also analyzed to determine drivers of utility differences.

To characterize the relationship between EQ-5D-5L utility score and select respondent characteristics, we employed post-Lasso ordinary least squares (OLS) regression, a supervised machine learning algorithm that has the advantage of enhanced prediction accuracy and interpretability in high-dimensional settings (p variables > n observations) by avoiding overfitting through post-regularization inference by the L1-norm.[20] Because this regularization also shrinks the model's fitted coefficients towards zero, causing a potentially significant bias,[21] we use the post-Lasso OLS estimator, introduced and analyzed by Belloni and Chernozhukov in 2013,[22] which has been shown to perform at least as well as Lasso in terms of the rate of convergence and has the advantage of a smaller bias, even if the Lasso-based model selection "fails" in the sense of missing some components of the "true" model (i.e., the best s-dimensional approximation to the nonparametric regression function chosen by the hypothetical all-knowing researcher). Additional details can be found in Belloni and Chernozhukov's paper.[22] The R package High-dimensional Metrics (hdm)[23] was employed to implement "rigorous" Lasso, which provides a theoretically grounded and data-driven choice of the penalty level λ in the Lasso regressions, and to generate efficient estimators and uniformly valid confidence intervals using post-Lasso OLS.[24]

Although we used a post-regularization inference model to mitigate bias from regularization, there is potential for unobserved confounding of our post-LASSO OLS estimates, i.e. a factor associated with both utility and the characteristics included in the model. To assess the required strength that any unmeasured confounder must have to attenuate our model estimates, we calculated the regression coefficient E-values in a sensitivity analysis. E-values indicate the "minimum strength of association, on the risk ratio (RR) scale, that an unmeasured confounder would need to have with both the treatment and outcome, conditional on the measured covariates, to fully explain away a specific treatment-outcome association."[25] The E-value is generally calculated as follows:

$$\text{E-value} = \text{RR} + \sqrt{RR \times (RR - 1)}$$

where RR is the relative risk. Since our utility outcome is continuous, effect-size conversions in Chinn (2000)[26] and VanderWeele (2017)[27] approximately convert the mean difference between hypothetical exposure "groups" to the odds ratio that would arise from dichotomizing the continuous outcome. Similarly, we use E-values to assess the strength of a potential confounder to expand the confidence interval to include the null (estimate=0).

Finally, we estimated QALY gain/loss by age group compared to population norms. We calculated the utility change compared to norms by age group, then multiplied this change by the total population in each age group to obtain population-wide change in utility. This calculation assumed that any detected utility change lasts 12 months. To examine the impact on number of lives lost, we divided the total QALY gain/loss by the estimated life expectancy for each age group to extrapolate total lives lost resulting from changes in HRQoL captured by the EQ-5D-5L.

Results

Sample

We received 2,776 complete responses to the EQ-5D-5L. Compared with the US general population, our sample was slightly older, with higher education and income; less Hispanic and Black respondents, but more individuals identifying as multi-race. There was also less chronic hypertension, diabetes, arthritis, and migraine; but more hypercholesterolemia, depression, asthma, and bronchitis (cancer). Full-time employment, gender, age, marital status, and BMI ≥30 were similar to the general US population (Table 1).

Most respondents reported working in management (9.6%), business and finance (11.9%), computer and mathematical industries (11.3%), and office/administrative support (10.3%). Less than 1% reported working in protective services, grounds maintenance, farming/fishing/forestry, or in the military. As a result of COVID-19, 52.8% reported no change in their employment, 31.9% reported working at home, 5.8% reported losing their jobs, and 9.6% reported being temporarily laid off. 8.8% reported that COVID-19 completely prevented them from working. Most (70.4%) reported no hours of missed work due to COVID-19.

When rating fear of COVID-19's impact on their health, 59.5% of the sample reported a score of ≥5 on a scale of 0-10 (mean 5.20, SD 2.95). When rating fear of COVID-19's impact on their economic/financial well-being, 67.6% reported a score of ≥5 (mean 5.79, SD 3.01). 90.8% of respondents were under mandatory social distancing, and 90.6% scored ≥5 (mean 8.37, SD 2.5) in support of social distancing policies to prevent the spread of COVID-19.

EQ-5D-5L

26.1% (n=720) reported no problems in any dimension. Among ages 18-24, the mean (SD) utility value was 0.752 (0.281), significantly lower compared to pre-pandemic (0.921 (0.124), p=0.01), online

(0.844 (0.184), p<0.001), and face-to-face EQ-5D-5L norms (0.919 (0.127), p<0.001). Among ages 25-34, utility was significantly worse compared to face-to-face norms (0.825 (0.235) vs. 0.911 (0.111), p<0.001); no significant differences were seen vs. online norms. Among ages 35-64, utility values were higher during-pandemic but only vs. online norms; there were no significant differences compared to pre-pandemic and face-to-face samples. At age 65+, utility values (0.827 (0.213)) were nearly identical across all samples.

For the VAS, all age groups except age 45-54 had significantly worse scores compared to face-to-face norms. Only ages 18-24 reported significantly worse mean VAS scores compared to online norms (73.1 vs. 79.9, p=0.001), and ages 25-34 reported significantly better scores compared to pre-pandemic (76.6 vs. 60.8, p=0.008). Pre-pandemic sample sizes for other age groups were too small (n<5) to draw meaningful inferences. All EQ-5D-5L and VAS comparisons between the MTurk sample and online and face-to-face samples are stratified by age group in Table 2.

Differences appear to be driven by the anxiety/depression dimension of the EQ-5D-5L. Compared to either norm, anxiety/depression was worse during-pandemic (Figure 1). In particular, females experienced more anxiety/depression than males, and those identifying as “other” gender reported even worse anxiety/depression (Supplemental Figure 1). When stratified by BMI, those who were underweight or obese experienced the most severe/extreme anxiety/depression (Supplemental Figure 2).

Predictors of EQ-5D-5L Utility

Table 3 displays the post-Lasso OLS regression results along with E-values for the point estimates and their confidence interval limits closer to the null. As expected, ages 25 years and older are significantly associated ($p \leq 0.05$) with higher EQ-5D-5L utility relative to ages 18-24. Compared to males, transgender persons have significantly lower utility scores, whereas females differ non-significantly from males. These differences by gender are driven by the anxiety and depression dimension (Supplemental Figure 1). Native Hawaiian/Pacific Islander is significantly associated with lower utility compared to being White, whereas all other race groups differ non-significantly from whites; Hispanic ethnicity is also significantly associated with lower utility, as is being married or living alone, compared to being single. Those who are underweight also report significantly worse utility than those with normal BMI; as with gender, this is driven mainly by anxiety/depression (Supplemental Figure 2). Similarly, lower utility scores were reported among those with arthritis, diabetes, stroke, depression, and/or migraine, or a family member diagnosed with COVID-19. Lastly, the level of fear of the pandemic’s impact on personal health is negatively and significantly correlated with utility. Other than age, only income levels above $50,000 are associated with significant increases in utility compared to incomes <$20,000.

While using a machine-learning algorithm robustly estimates significant predictors of EQ-5D-5L utility, we also calculated E-values for each coefficient to quantify unmeasured confounding. Several of our model coefficients have significant p-values, but none have an E-value confidence limit greater than RR=2.5, suggesting that, conditional on our measured covariates, an unobserved confounder associated with both EQ-5D-5L utility and a given predictor by a relative risk factor of up to 2.5 could attenuate our estimated effects.[28]

Population QALY Loss

When extrapolated to the US population, we calculated an overall loss of 2.6 million QALYs compared to the pre-pandemic sample, a gain of 3.5 million QALYs compared to the online norm, and a loss of 8.4 million QALYs compared to the face-to-face norm. After dividing these values by life expectancy for each age group, we calculated an overall average gain of 18,385 lives at the expense of those aged 18-34. This was driven primarily by younger age groups, with average lives lost of 77,343 and 32,449 for 18-24 and 25-34 years old, respectively (Table 4).

Discussion

Despite differences in demographic characteristics compared to the US population (i.e. slightly older, higher income and education levels), HRQoL has decreased during COVID-19 compared to US population norms, especially for younger population aged 18-24. This is unsurprising as the younger generation is likely more anxious about the future (education, career) and less firmly established in a set employment/career path. In addition, younger adults are at a critical life stage in developing and solidifying social relationships and networks, and social distancing/lockdowns due to COVID-19 has had a disproportionate impact on them, particularly as this age group is much less likely to be directly impacted by mortality due to COVID-19, with a reported 190 deaths among those aged 15-24 and 935 deaths among those aged 25-34 years, compared to the 130,250 total COVID-19 deaths reported to the CDC for the week ending July 11, 2020.

Although HRQoL was higher than population norms among other age groups, this may reflect a healthier, more highly educated sample compared to the US general population. This may be due to factors such as the ability to work from home without loss of pay, spending more time with family and friends, and more flexibility allowing time for non-job-related tasks. Nonetheless, results suggest that the mental health impact of COVID-19 is significant. It is difficult if not impossible to disentangle the positive and negative impact of these elements, and it is also important to acknowledge that relationship between these factors and HRQoL may change as the pandemic continues.

In examining predictors of utility, we used a robust machine-learning algorithm rather than traditional regression models to identify significant associations between respondent characteristics and HRQoL. Doing so allows for the robust estimation of significant predictors of EQ-5D-5L utility, given the data collected in our survey. Because such prediction is only as valid as the data collected (and is thus conditional on observable factors), we calculated E-values for all coefficients to determine the extent to which unmeasured confounding could have explained the results, and found that relatively strong unmeasured confounding (RR=2.5) would be required to attenuate our observed results.

Maheswaran et al performed a similar multivariate analysis of sociodemographic and behavioral predictors of EQ-5D utility using the responses of a 2008 general population survey in England.[29] Most predictors examined by Maheswaran et al were included in our regression model, but they also reported estimates for some potential confounders that we did not include, such as alcohol consumption, smoking, fruit and vegetable intake, and physical activity. Among these, only one factor (being physically inactive) explored by Maheswaran et al has an effect size upper bound of RR>2.5. Given this, and the fact that we demonstrate relatively good covariate control in our model, our estimates are robust to unobserved confounders like alcohol, smoking, diet, and exercise. Since Maheswaran et al's study is based on an EQ-5D-5L survey of the general population (much like ours) in England (culturally similar to the US) and adjusts for most of the factors included in our regression, we find it is a good fit for contextualizing the E-values of our estimates.

A key limitation is that our sample was restricted to the online MTurk platform. The platform has been shown to have mixed external validity to the general population depending on context.[19,30–33] Despite this limitation, we believe our results are likely an underestimate of HRQoL in the general population as MTurk workers are more likely to be those who have the flexibility to complete online tasks, and thus less likely to live and work in situations that would be heavily impacted by COVID-19, such as job loss or furlough. Nationally, reported unemployment rates reached a high of nearly 15% in April and have remained in double digits since, yet some metropolitan areas have reported numbers >30%.[34,35] These numbers are far higher than the 5.8% who reported job loss and the 9.6% who reported being temporarily laid off in our sample. As seen from the employment characteristics of our sample, respondents were more likely to work in jobs that can be done remotely. It is therefore likely that those who experience significant job loss and/or loss income, and thus more likely to report worse HRQoL, are not being adequately captured in our sample.

Conclusion

We found that the HRQoL impact of COVID-19 on Americans varied by age group, with the largest negative impact on young adults aged 18-24 years. In contrast, HRQoL was similar or better in older adults compared to pre-COVID-19/previous population norms, particularly with respect to mental health. These results suggest public health policy has been implemented at the expense of the mental well-being of younger adults whose health outcomes have been discounted relative to the elderly based on policy initiatives to date. It is important to consider the long-term implications of such policies moving forward as the government begins to re-open the country.

Declarations

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CONFLICT OF INTEREST STATEMENT

Dr. Pickard reports that he is a partner in a health care consulting company, Second City Outcomes Research LLC, but that work has no bearing on the content of this manuscript. I am an association member of the EuroQol Research Foundation, a Dutch registered charity that provide some financial support for data collection. Mr. Crawford reports grants from EuroQol Foundation during the conduct of the study. All other authors report no other conflicts of interest.

Ethics

Human subjects approval was obtained through the University of Southern California Institutional Review Board # UP-20-00267. Consent: Each participant consented to participation.

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Tables

Table 1: Sample Demographics vs. US Population

	Sample, n (%)	US Population (%)	Reference
Age (median, years)	40	38.3	US Census Bureau[36]
Gender			US Census Bureau[36]
Male	1380 (48.7)	49.1	
Female	1424 (50.2)	50.8	
Other	30 (1.1)	NA	
Race			US Census Bureau[37]
White	1964 (69.1)	76.5	
Black	209 (7.4)	13.4	
Asian	192 (6.8)	5.9	
Pacific Islander	4 (0.1)	0.2	
Multi-race	412 (14.5)	2.7	
Other	45 (1.9)	NA	
American Indian or Alaska Native	18 (0.6)	1.3	
Hispanic Ethnicity	279 (9.8)	18.3	US Census Bureau[37]
Education			US Census Bureau[38]
Less than high school degree	15 (0.5)	10.6	-
High school degree or equivalent	279 (9.8)	28.3	-
Some college but no degree	479 (16.9)	18	-
Associate degree	324 (11.4)	9.8	-
Bachelor degree	1251 (44.0)	21.3	-
Graduate degree	495 (17.4)	12	-
Marital status			US Census Bureau[39]
Single	1103 (38.9)	33.8	
Married	1328 (46.8)	47.8	
Separated	27 (1.0)	1.9	
Divorced	277 (9.8)	10.9	

Widowed	77 (2.7)	5.7	
Prefer not to say	26 (0.9)		
Income			US Census Bureau[40]
Less than $20,000	247 (9.9)	14.7	
$20,000 to $34,999	286 (10.3)	13.2	
$35,000 to $49,999	425 (15.3)	12	
$50,000 to $74,999	491 (17.7)	17.2	
$75,000 to $99,999	702 (25.3)	12.5	
$100,000 to $149,999	441 (15.9)	14.9	
Over $150,000	309 (11.1)	15.5	
Insurance			
Private	380 (47.6)	55.1	Kaiser Family Foundation[41]
Medicare	114 (14.3)	17.4	US Census Bureau[42]
Medicaid	83 (10.4)	17.9	
ACA	64 (8.0)	3.3	
Self-pay	30 (3.8)	10.8	
None	121 (15.1)	8.5	
Don’t know	7 (0.9)	NA	
Political Affiliation			Gallup Poll[43]
Republican	781 (28.8)	27	-
Democrat	1273 (47.0)	31	
Independent	636 (23.5)	39	
None	20 (0.7)	NA	
Live Alone			US Census Bureau[44]
Yes	600 (26.0)	26	
No	1713 (74.1)	74	
Medical History			
Cholesterol	399 (15.4)	11.8	CDC[45]

Hypertension	429 (16.6)	33.2	CDC[46]
Arthritis	270 (10.4)	23.7	CDC[47]
Diabetes	212 (8.2)	10.5	CDC[48]
Heart failure	53 (2.0)	2.4	CDC[49]
Stroke	60 (2.3)	3.1	CDC[50]
Bronchitis	155 (6.0)	3.6	CDC[51]
Asthma	329 (12.7)	7.7	CDC[52]
Depression	607 (23.4)	7.6	CDC[53]
Migraine	251 (9.7)	15.9	CDC[54]
Cancer	267 (10.3)	9.4	CDC[55]
Tobacco Use			CDC[56,57]
Current	370 (16.7)	14	
Previous	685 (30.9)	21.3	-
Never	1164 (52.5)	64.7	
BMI			DQYDJ[58]; CDC[59]
<18.5	164 (5.9)	1.6	
18.5 - 24.9	897 (32.1)	27.5	
25.0 - 29.9	654 (23.4)	31.6	-
≥30	1077 (38.6)	39.4	-
Employment			US Census Bureau[60]
Full-time	1614 (58.6)	59.8	-
Part-time	439 (16.0)		
Unemployed seeking	176 (6.4)	4.9	
Unemployed not seeking	107 (3.9)		
Student	66 (2.4)		
Retired	219 (8.0)		
Disability	35 (1.3)		

Homemaker	94 (3.4)
Don’t know	4 (0.2)

Table 2: Comparison of EQ-5D-5L Utility Values and VAS Scores to Norms

EQ-5D-5L MEAN UTILITY VALUES							
	DURING	**PRE**		**ONLINE**		**F2F***	
Age	**(n=2,746)**	**(n=40)**	**p-value**	**(n=2,018)**	**p-value**	**(n=1,134)**	**p-value**
18-24	0.752	0.921	**0.010**	0.844	**0.000**	0.919	**0.000**
25-34	0.825	0.860	0.490	0.811	0.305	0.911	**0.000**
35-44	0.845	0.867	0.393	0.794	**0.001**	0.841	0.806
45-54	0.818	0.736	0.452	0.760	**0.001**	0.816	0.969
55-64	0.817	0.766	0.543	0.781	**0.022**	0.815	0.996
>=65	0.827	0.831	0.957	0.831	0.815	0.819	0.707
EQ-5D-5L MEAN VAS SCORES							
	DURING	**PRE**		**ONLINE**		**F2F**	
Age	**(n=2,746)**	**(n=40)**	**p-value**	**(n=2,018)**	**p-value**	**(n=1,134)**	**p-value**
18-24	73.1	72.3	0.950	79.9	**0.001**	84.9	**0.000**
25-34	76.6	60.8	**0.008**	77.7	0.261	84.4	**0.000**
35-44	74.2	74.9	0.894	74.7	0.686	78.1	**0.004**
45-54	73.2	70.5	0.709	71.1	0.172	75.9	0.101
55-64	73.4	71.0	0.827	71.5	0.194	78.8	**0.002**
>=65	74.4	67.3	0.073	75.1	0.696	80.9	**0.000**

Bolded values indicate statistical significance ($p < 0.05$).

TABLE 3: Relationship between EQ-5D Utility Score and Select Respondent Characteristics, estimated by post-LASSO OLS regression

	Coefficient (95% CI)	P-value	E-value (95% CL)
Intercept	0.949		
Gender			
Male (reference)	–	–	–
Female	0.009 (-0.009, 0.026)	0.339	1.23 (1.00)
Transgender	-0.196 (-0.325, -0.067)	0.003	1.96 (1.00)
Prefer not to say	-0.067 (-0.190, 0.057)	0.291	3.92 (1.97)
Age			
18-24 (reference)	–	–	–
25-34	0.048 (0.014, 0.083)	**0.006**	1.74 (1.31)
35-44	0.066 (0.029, 0.102)	**<0.001**	1.95 (1.51)
45-54	0.057 (0.016, 0.098)	**0.006**	1.85 (1.35)
55-64	0.065 (0.026, 0.105)	**0.001**	1.95 (1.46)
>=65	0.088 (0.043, 0.134)	**<0.001**	2.24 (1.68)
Race			
White (reference)	–	–	–
American Indian or Alaska Native	0.076 (-0.024, 0.177)	0.135	2.09 (1.00)
Asian	0.023 (-0.009, 0.055)	0.166	1.43 (1.00)
Black or African American	-0.018 (-0.050, 0.013)	0.260	1.37 (1.00)
Native Hawaiian or other Pacific Islander	-0.239 (-0.432, -0.045)	**0.016**	1.45 (1.00)
Multi-race	-0.025 (-0.078, 0.028)	0.361	4.80 (1.71)
Other	0.063 (-0.018, 0.145)	0.128	1.92 (1.00)

Prefer not to say	0.055 (-0.068, 0.179)	0.381	1.82 (1.00)
Hispanic ethnicity			
No (reference)	–	–	–
Yes	-0.061 (-0.091, -0.031)	**<0.001**	1.24 (1.00)
Prefer not to say	0.009 (-0.088, 0.106)	0.853	1.90 (1.53)
Marital status			
Single (reference)	–	–	–
Married	-0.035 (-0.057, -0.013)	**0.002**	1.12 (1.00)
Separated	-0.030 (-0.116, 0.056)	0.492	1.58 (1.30)
Divorced	-0.003 (-0.034, 0.029)	0.861	1.27 (1.00)
Widowed	0.011 (-0.040, 0.063)	0.662	1.52 (1.00)
Prefer not to say	0.011 (-0.086, 0.108)	0.819	1.27 (1.00)
Annual income			
Less than $20,000 (reference)	–	–	–
$20,000 to $34,999	0.021 (-0.014, 0.055)	0.245	1.40 (1.00)
$35,000 to $49,999	0.030 (-0.004, 0.064)	0.082	1.52 (1.00)
$50,000 to $74,999	0.062 (0.029, 0.095)	**<0.001**	1.91 (1.51)
$75,000 to $99,999	0.051 (0.016, 0.087)	**0.004**	1.78 (1.34)
$100,000 to $149,999	0.061 (0.022, 0.100)	**0.002**	1.89 (1.42)
Over $150,000	0.103 (0.053, 0.153)	**<0.001**	2.44 (1.80)
Education			
Less than high school degree (reference)	–	–	–

High school degree or equivalent (e.g., GED)	0.092 (-0.028, 0.212)	0.132	2.29 (1.00)
Some college but no degree	0.075 (-0.043, 0.194)	0.213	2.07 (1.00)
Associate degree	0.091 (-0.028, 0.211)	0.134	2.27 (1.00)
Bachelor degree	0.064 (-0.053, 0.182)	0.283	1.93 (1.00)
Graduate degree	0.085 (-0.034, 0.204)	0.162	2.19 (1.00)
Live alone	-0.038 (-0.060, -0.016)	**<0.001**	1.61 (1.34)
BMI			
Normal (reference)	–	–	–
Underweight	-0.113 (-0.151, -0.075)	**<0.001**	1.23 (1.00)
Overweight	0.006 (-0.014, 0.026)	0.573	1.18 (1.00)
Obese	-0.008 (-0.031, 0.014)	0.475	2.57 (2.07)
High cholesterol	-0.002 (-0.027, 0.023)	0.866	1.10 (1.00)
Hypertension	-0.023 (-0.047, 0.002)	0.069	1.42 (1.00)
Arthritis	-0.112 (-0.140, -0.083)	**<0.001**	2.55 (2.17)
Diabetes	-0.092 (-0.123, -0.061)	**<0.001**	2.29 (1.89)
Heart failure	-0.056 (-0.122, 0.010)	0.097	1.83 (1.00)
Stroke	-0.182 (-0.255, -0.108)	**<0.001**	3.65 (2.50)
Bronchitis	0.001 (-0.039, 0.041)	0.958	1.07 (1.00)
Asthma	-0.025 (-0.053, 0.003)	0.078	1.46 (1.00)
Depression	-0.118 (-0.138, -0.097)	**<0.001**	2.63 (2.36)
Migraine	-0.053 (-0.082,	**<0.001**	1.80

	-0.025)		(1.45)
Cancer	-0.014 (-0.057, 0.028)	0.513	1.31 (1.00)
Experienced COVID-19-like symptoms not serious enough to require hospitalization	-0.027 (-0.055, 0.002)	0.071	1.48 (1.00)
Has a family member diagnosed with COVID-19	-0.087 (-0.126, -0.048)	**<0.001**	2.22 (1.74)
Knows someone with a COVID-19 diagnosis	-0.007 (-0.029, 0.014)	0.507	1.21 (1.00)
Fear of COVID-19's impact on health (1-10 scale)	-0.009 (-0.012, -0.005)	**<0.001**	1.23 (1.17)
Fear of COVID-19's impact on finances (1-10 scale)	-0.002 (-0.005, 0.002)	0.306	1.09 (1.00)

Abbreviations: OLS—ordinary least squares; CI—confidence interval; CL—confidence limit; BMI—body mass index; COVID-19—Coronavirus disease 2019. Bolded values indicate significance at the 0.05 level.

Table 4: Change in QALYs and Lives Affected

TOTAL CHANGE IN QALYs					
Age	**US Population**	**PRE**	**ONLINE**	**F2F**	**AVERAGE**
18-24	31,678,500	-5,340,457	-2,917,051	-5,292,939	-4,516,816
25-34	45,209,000	-1,548,922	649,879	-3,871,021	-1,590,021
35-44	41,027,000	-920,509	2,081,300	153,031	437,940
45-54	40,700,000	3,353,599	2,366,624	87,424	1,935,882
55-64	41,755,000	2,130,799	1,483,597	63,927	1,226,108
>=65	52,787,000	-225,999	-208,403	425,041	-3,120
TOTAL QALY CHANGE		-2,551,488	3,455,945	-8,434,537	-2,510,027
TOTAL CHANGE IN LIVES					
Age	**Life Expectancy (years remaining)**	**PRE**	**ONLINE**	**F2F**	**AVERAGE**
18-24	58.40	-91,446	-49,950	-90,633	-77,343
25-34	49.00	-31,611	13,263	-79,000	-32,449
35-44	39.80	-23,128	52,294	3,845	11,004
45-54	30.8	108,883	76,838	2,838	62,853
55-64	22.50	94,702	65,938	2,841	54,494
>=65	18	-12,555	-11,578	23,613	-173
TOTAL LIVES AFFECTED		44,845	146,805	-136,495	18,385

*F2F: face-to-face

Figures

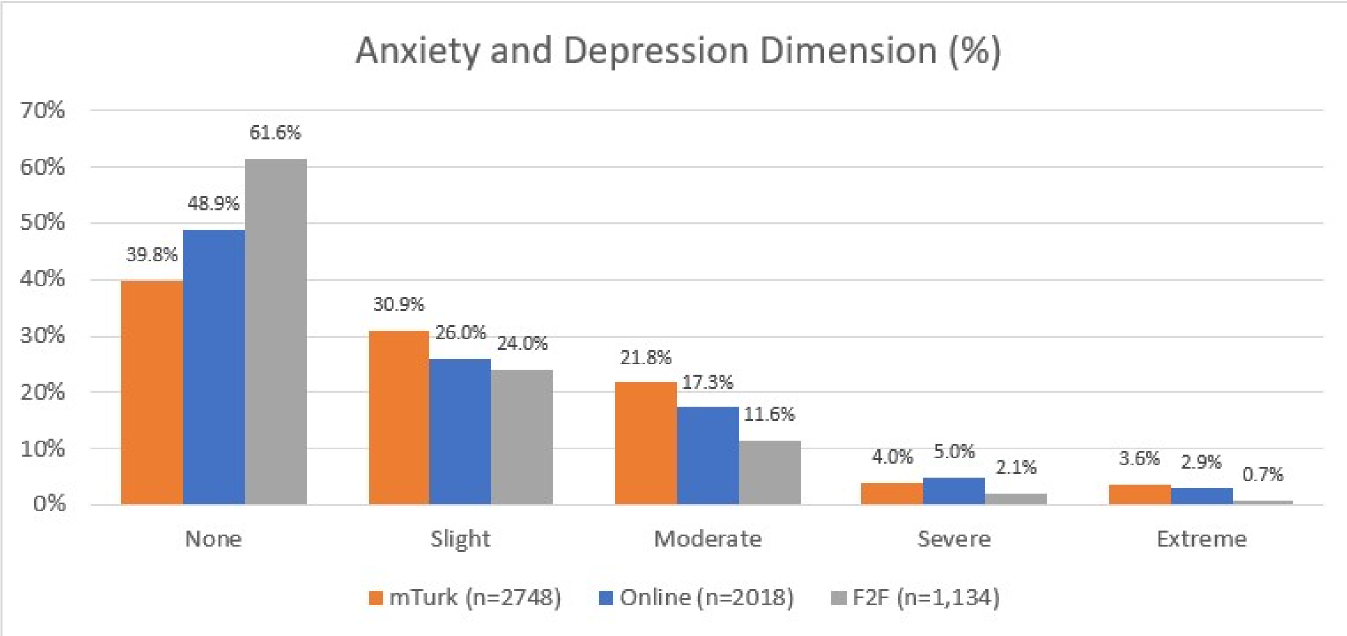

Figure 1

Anxiety and Depression Dimension. Percentage of individuals reporting none, slight, moderate, severe, and extreme problems with anxiety and depression by cohort. The during-pandemic cohort reports more problems than either online or face-to-face norms.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementalFigures.docx