A US Population Health Survey on the Impact of COVID-19 Using the EQ-5D-5L

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BACKGROUND: The COVID-19 pandemic has resulted in negative impacts on the economy, population health, and health-related quality-of-life (HRQoL).

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

DESIGN: We surveyed respondents on physical and mental health, demographics, socioeconomics, brief medical history, current COVID-19 status, sleep, dietary, financial, and spending changes. Results were compared to online and face-to-face US population norms. Predictors of EQ-5D-5L utility were analyzed using both standard and post-lasso OLS regressions. Robustness of regression coefficients against unmeasured confounding was analyzed using the E-Value sensitivity analysis.

SUBJECTS: Amazon MTurk workers (n=2776) in the USA.

MAIN MEASURES: EQ-5D-5L utility and VAS scores by age group.

KEY RESULTS: We received n=2746 responses. Subjects 18–24 years reported lower mean (SD) health utility (0.752 (0.281)) compared with both 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). For ages 35–64, utility was better during pandemic compared to 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. VAS scores were worse for all age groups (p<0.005) except ages 45–54. Increasing age and income were correlated with increased utility, while being Asian, American Indian or Alaska Native, Hispanic, married, living alone, having history of chronic illness or self-reported depression, experiencing COVID-19-like symptoms, having a family member diagnosed with COVID-19, fear of COVID-19, being underweight, and living in California were associated with worse utility scores. Results were robust to unmeasured confounding.

CONCLUSIONS: HRQoL decreased during the pandemic compared to US population norms, especially for ages 18–24. The mental health impact of COVID-19 is significant and falls primarily on younger adults whose health outcomes may have been overlooked based on policy initiatives to date.

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INTRODUCTION

The COVID-19 global pandemic has resulted in exceptional societal disruption, 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 November 24, 2020, a simple PubMed search of "covid 19 depression" yields 1,457 results, with studies using validated measures indicating increased levels of anger, depression, anxiety, and stress both within and outside the USA. With global lockdown policies of varying severities and the cancelations/closures of events, businesses, and entertainment venues, it is abundantly clear that the pandemic has significantly impacted quality-of-life of individuals worldwide, and has especially exacerbated mental health issues, including those of clinicians and healthcare workers (HCWs), who are responsible for treating mental health issues in the general public.[11–13]

Missing from the COVID-19 literature in the USA is a standardized measure for health-related quality-of-life (HRQoL) that allows comparisons across different disease states and conditions such as the EQ-5D-5L, a generic health measure that is globally used in population health studies and economic evaluations because of its generalizability and ease of administration.[14] It is short, simple, and validated in both online and face-to-face panels in the USA.[15–17] Respondents rate mobility, self-care, usual activities, pain/discomfort, and anxiety/depression on a scale of 1–5 indicating no to extreme problems. Responses can be converted into health utility scores by applying a societal preference function which generates scores anchored at 0 for death and 1 for perfect health, representing a societal valuation of HRQoL; these scores can be used to calculate quality-adjusted life years (QALYs) to guide health technology assessment. Also included is a Visual Analog Scale (VAS), asking respondents to self-rate their overall health on a scale of 0–100, thus directly reflecting HRQoL as valued by respondents.[15] The EQ-5D-5L has been validated in hundreds of countries and languages, providing a standardized approach to measure and compare health within and across nations.[15]

Since the pandemic began, the EQ-5D-5L has been used to assess HRQoL in the Netherlands,[18] Germany,[19] France,[20] Morocco,[21] China,[22] Hong Kong,[23] Vietnam,[24] and Spain[25] in various contexts including the general public, those with specific diseases, and healthcare providers; these studies have shown an overall decline in HRQoL, and pronounced worsening of anxiety and depression. The 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 USA (n=2,776). Amazon's Mechanical Turk (MTurk) platform[26] was used to survey respondents on demographics, COVID-19 status, and behavior and employment changes related to COVID-19 (Supplementary material). MTurk is an online crowd-sourced platform that allows large-scale surveys to be deployed, and thus can be useful for clinical research.[27, 28] Anyone >18 years of age can register as a respondent, known as a "Worker," to voluntarily complete "Human Intelligence Tasks" (HITs) according to criteria set by the research team, such as age or sex. HITs are activities requiring human input, such as image processing, data verification, surveys, and data processing (e.g., translation, transcribing audio content).[26] Because the platform is online, all tasks require an active internet connection. In our study, all Workers were eligible as long as they resided in the USA, and were given $2 compensation for their time. Our only inclusion criteria were to ensure that age and gender across respondents was similar to US census data.

We surveyed respondents on HRQoL using the EQ-5D-5L. We also included questions on demographics, brief medical history, socioeconomic status, current COVID-19 status, and employment status. Finally, we 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 ensure a relatively even distribution of sample respondents across age and gender similar to the general US population (Table 1). Criteria restricting respondents to those aged 55+ was added after the initial 2000 subjects were recruited to improve the age representativeness of the sample.

Demographics were compared to the general population based on US census data. Utility values were calculated from EQ-5D-5L responses using US-derived value weights.[17] 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.[16] We used t-tests and chi-square tests for numeric and categorical variables respectively to identify statistically significant differences.

We employed standard ordinary least squares (OLS) regression to evaluate the impact of demographic characteristics, personal C19 symptoms, diagnosis of COVID-19 in family, knowing someone with a COVID-19 diagnosis, and fear of health and financial consequences (full list, Table 3) on EQ-5D-5L utility score. To improve model fit, we included additional predictors such as BMI category, disease history (hypercholesterolemia, hypertension, arthritis, diabetes, heart failure, stroke, bronchitis, asthma, self-reported depression, migraine, and cancer), and US state of residence, as well as all two-way interactions between predictors. Because of the high number of predictors relative to number of responses, we then employed lasso regression, a supervised machine learning algorithm that reduces overfitting and multicollinearity.[29] We constrained lasso from regularizing the characteristics of interest listed above and employed 10-fold cross-validation to minimize mean squared error (MSE). Details are described in the Technical Appendix.

Of the variables not constrained from regularization, lasso selected three predictors and two interactions: arthritis, diabetes, self-reported depression, stroke interacted with fear of COVID-19's impact on health (1–10 scale), and underweight BMI interacted with residing in California. Since lasso coefficients are biased and not intended for inference,[30] we fit a second OLS model to obtain unbiased coefficients on these selected predictors (full variable list, Table 4).

For inference, the coefficients given by the second (post-lasso) OLS regression were bootstrapped 500 iterations to estimate standard errors, computed as the standard deviation of the bootstrap replicates.[30] The standard errors were then used to construct normal-theory 97.5% confidence intervals for the regression coefficients, using the Bonferroni correction to compare the results of the two OLS models. We report the median bootstrap estimates as the post-lasso OLS point estimates with the normal-theory

Table 1 Sample Demographics vs. US Population

	Sample, *n* (%) *N*=2,746	US population (%)	Reference
Age (median, years)	39	38.3	US Census Bureau[42]
Gender			US Census Bureau[42]
Male	1342 (48.9)	49.1	
Female	1365 (49.7)	50.8	
Transgender	13 (0.5)		
Other/prefer not to say	17 (0.6)	NA	
Missing	9 (0.3)		
Race			US Census Bureau[43]
White	1,888 (68.8)	76.5	
Black	200 (7.3)	13.4	
Asian	188(6.9)	5.9	
Native Hawaiian/Pacific Islander	4 (0.2)	0.2	
Multi-race	405 (14.8)	2.7	
Other	26 (1.0)	NA	
American Indian or Alaska Native	17 (0.6)	1.3	
Hispanic Ethnicity		18.3	US Census Bureau[43]
Yes	272 (9.9)		
No	2,452 (89.3)		
Prefer not to say	20 (0.7)		
Missing	2 (0.1)		
Education			US Census Bureau[44]
Less than high school degree	14 (0.5)	10.6	
High school degree or equivalent	264 (9.6)	28.3	
Some college but no degree	457 (16.6)	18	
Associate degree	316 (11.5)	9.8	
Bachelor degree	1,212 (44.1)	21.3	
Graduate degree	483 (17.6)	12	
Marital status			US Census Bureau[45]
Single	1,073 (39.1)	33.8	
Married	1,284(46.8)	47.8	
Separated	23 (0.8)	1.9	
Divorced	266 (9.7)	10.9	
Widowed	75 (2.7)	5.7	
Prefer not to say	25 (0.9)		
Income			US Census Bureau[46]
Less than \$20,000	278 (10.1)	14.7	
\$20,000 to \$34,999	425 (15.5)	13.2	
\$35,000 to \$49,999	482 (17.6)	12	
\$50,000 to \$74,999	694 (25.3)	17.2	
\$75,000 to \$99,999	441 (16.1)	12.5	
\$100,000 to \$149,999	306 (11.1)	14.9	
Over \$150,000	118 (4.3)	15.5	
Missing	2 (0.1)		
Insurance			
Private	377 (13.8)	55.1	Kaiser Family Foundation[47]
Medicare	114 (4.2)	17.4	US Census Bureau[48]
Medicaid	83 (3.0)	17.9	
ACA	64 (2.3)	3.3	
Self-pay	30 (1.1)	10.8	
None	119 (4.3)	8.5	
Don't know	7 (0.3)	NA	
Missing	1,952(71.1)		
Political Affiliation			Gallup Poll[49]
Republican	778 (28.3)	27	
Democrat	1,248 (45.5)	31	
Independent	631 (23.0)	39	
None	20 (0.7)	NA	
Missing	69 (2.5)		
Live Alone			US Census Bureau[50]
Yes	592 (21.6)	26	
No	1,694 (61.7)	74	
Missing	460(16.8)		
Medical History			
Cholesterol	408 (14.9)	11.8	CDC[51]
Hypertension	438 (16.0)	33.2	CDC[52]
Arthritis	278 (10.1)	23.7	CDC[53]
Diabetes	214 (7.8)	10.5	CDC[54]
Heart failure	56 (2.0)	2.4	CDC[55]
Stroke	61 (2.2)	3.1	CDC[56]
Bronchitis	155 (5.6)	3.6	CDC[57]
Asthma	329 (12.0)	7.7	CDC[58]
Depression	599 (21.8)	7.6	CDC[59]
Migraine	248 (9.0)	15.9	CDC[60]
Cancer	268 (9.8)	9.4	CDC[61]
Missing	198 (7.2)		
Tobacco Use			CDC[62, 63]
Current	368 (13.4)	14	
Previous	686 (25.0)	21.3	
Never	1,148 (41.8)	64.7	
Missing	543(19.8)		
BMI			DQYDJ[64]; CDC[65]
<18.5	163 (5.9)	1.6	
18.5–24.9	881 (32.1)	27.5	
25.0–29.9	652 (23.8)	31.6	
≥30	507 (18.5)	39.4	
Missing	543(19.8)		
Employment			US Census Bureau[66]
Full-time	1605 (58.5)	59.8	
Part-time	439 (16.0)		
Unemployed seeking	174 (6.3)	4.9	
Unemployed not seeking	105 (3.8)		
Student	64 (2.3)		
Retired	225 (8.1)		
Disability	34 (1.2)		
Homemaker	87(3.2)		
Don't know	4 (0.2)		
Missing	9(0.3)		

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Table 1. (continued)

bootstrap intervals. A partial *F*-test was employed to determine whether the post-lasso model significantly fits the data better than the standard model.

Since this is a non-randomized study, there is potential for unmeasured confounding to bias our estimated associations between respondent characteristics and quality-of-life. We therefore calculated regression coefficient *E*-values to assess the required strength that any unmeasured confounder must have to nullify our model's statistically significant findings

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**

Utility values represent societal preference scores for the health states as rated by respondents and can be used to calculate quality-adjusted life years (QALYs). VAS scores directly reflect the respondents' valuation of his/her own health status. Bold values indicate statistical significance ($p < 0.05$)

(see Technical Appendix).[31, 32] R version 4.0.1 was used to perform statistical analyses with significance set at 0.05.

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. We then 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 2,746 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/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 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

Among ages 18–24 (*n*=198), 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 (*n*=817), 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 (*n*=1,488), 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+ (*n*=248), 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, which was worse during pandemic vs. either norm (Fig. 1). This was especially pronounced among females and "other" gendered persons

Table 3 Relationship Between EQ-5D Utility Score and Select Respondent Characteristics, Estimated by OLS Regression

Predictor	Estimate	Lower 97.5% CI	Upper 97.5% CI	Std. error	*P* value*	*E*-value	*E*-value 95% CL
(Intercept)	0.801	0.649	0.952	0.067	<0.001	54.162	31.309
Gender, male	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)
Gender, female	−0.011	−0.032	0.010	0.009	0.246	1.267	1.000
Gender, prefer not to say	−0.095	−0.245	0.055	0.067	0.157	2.324	1.000
Gender, other	−0.203	−0.363	−0.044	0.071	0.004	4.055	1.932
Age group, 18–24	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)
Age group, 25–34	0.063	0.019	0.106	0.019	0.001	1.918	1.467
Age group, 35–44	0.078	0.033	0.124	0.020	<0.001	2.104	1.626
Age group, 45–54	0.058	0.008	0.109	0.023	0.010	1.857	1.297
Age group, 55–64	0.063	0.014	0.112	0.022	0.004	1.918	1.391
Age group, ≥65	0.083	0.029	0.138	0.024	0.001	2.168	1.592
Race, White	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)
Race, American Indian or Alaska Native	0.109	−0.015	0.234	0.055	0.048	2.513	1.083
Race, Asian	0.045	0.006	0.085	0.018	0.010	1.700	1.249
Race, Black or African American	−0.004	−0.043	0.034	0.017	0.807	1.147	1.000
Race, multiple-race	−0.055	−0.120	0.010	0.029	0.058	1.821	1.000
Race, Native Hawaiian or Other Pacific Islander	−0.205	−0.446	0.036	0.107	0.057	4.094	1.000
Race, other	0.084	−0.017	0.184	0.045	0.061	2.181	1.000
Race, prefer not to say	0.114	−0.039	0.268	0.068	0.095	2.583	1.000
Hispanic ethnicity, no	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)
Hispanic ethnicity, prefer not to say	0.002	−0.137	0.141	0.062	0.974	1.100	1.000
Hispanic ethnicity, yes	−0.056	−0.093	−0.018	0.017	0.001	1.833	1.427
Marital status, single	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)
Marital status, divorced	−0.004	−0.044	0.035	0.018	0.807	1.147	1.000
Marital status, married	−0.045	−0.072	−0.018	0.012	<0.001	1.700	1.412
Marital status, prefer not to say	0.035	−0.085	0.154	0.053	0.513	1.579	1.000
Marital status, separated	−0.042	−0.148	0.064	0.047	0.374	1.664	1.000
Marital status, widowed	−0.004	−0.068	0.060	0.029	0.881	1.147	1.000
Annual income, less than $20,000	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)
Annual income, $20,000 to $34,999	0.032	−0.011	0.074	0.019	0.094	1.543	1.000
Annual income, $35,000 to $49,999	0.050	0.008	0.092	0.019	0.008	1.760	1.294
Annual income, $50,000 to $74,999	0.085	0.044	0.125	0.018	<0.001	2.193	1.758
Annual income, $75,000 to $99,999	0.077	0.033	0.120	0.020	<0.001	2.092	1.614
Annual income, $100,000 to $149,999	0.097	0.048	0.145	0.022	<0.001	2.350	1.808
Annual income, over $150,000	0.146	0.084	0.207	0.028	<0.001	3.057	2.274
Education, less than high school degree	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)
Education, High school degree or equivalent (e.g., GED)	0.050	−0.099	0.199	0.066	0.451	1.760	1.000
Education, some college but no degree	0.027	−0.120	0.174	0.066	0.679	1.481	1.000
Education, associate degree	0.035	−0.114	0.183	0.066	0.601	1.579	1.000
Education, bachelor degree	0.024	−0.123	0.170	0.065	0.718	1.443	1.000
Education, graduate degree	0.031	−0.117	0.180	0.066	0.633	1.531	1.000
Live alone	−0.033	−0.061	−0.005	0.012	0.008	1.555	1.244
Experienced COVID-19-like symptoms not serious enough to require hospitalization	−0.039	−0.074	−0.003	0.016	0.014	1.628	1.215
Has a family member diagnosed with COVID-19	−0.090	−0.138	−0.042	0.021	<0.001	2.258	1.747
Knows someone with a COVID-19 diagnosis	−0.012	−0.039	0.014	0.012	0.294	1.282	1.000
Fear of COVID-19's impact on health (1–10 scale)	−0.013	−0.017	−0.009	0.002	<0.001	1.296	1.238
Fear of COVID-19's impact on finances (1–10 scale)	−0.002	−0.006	0.002	0.002	0.191	1.100	1.000

Abbreviations: OLS ordinary least squares, CI confidence interval, CL confidence limit, BMI body mass index, COVID-19 coronavirus disease 2019
**Significance level: 0.025*

(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 standard OLS regression results along with *E*-values for the point estimates and their confidence interval limits closer to the null. Compared to males, "other" gendered persons have significantly lower utility scores, whereas females and "prefer not to say" gendered persons differ non-significantly from males. Being 25+ years old was significantly associated ($p \leq 0.025$) with higher EQ-5D-5L utility relative to ages 18–24. Asian, American Indian, or Alaska Native race was significantly associated with lower utility compared to being White; other race groups differed non-significantly from Whites. Hispanic ethnicity was also significantly associated with lower utility, as was being married,

Table 4 Relationship Between EQ-5D Utility Score and Select Respondent Characteristics, Estimated by OLS Regression Following Lasso

Predictor	Estimate*	Lower 97.5% CI*	Upper 97.5% CI*	Std. error*	*E*-value	*E*-value 95% CL
(Intercept)	0.851	0.709	0.975	0.059	66.702	41.220
Gender, male	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)
Gender, female	0.002	−0.018	0.021	0.009	1.100	1.000
Gender, prefer not to say	−0.082	−0.186	0.030	0.048	2.155	1.000
Gender, other	−0.190	−0.445	0.083	0.118	3.808	1.000
Age group, 18–24	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)
Age group, 25–34	0.060	0.015	0.108	0.021	1.881	1.378
Age group, 35–44	0.071	0.025	0.120	0.021	2.017	1.517
Age group, 45–54	0.055	0.004	0.109	0.023	1.821	1.252
Age group, 55–64	0.066	0.019	0.117	0.022	1.955	1.430
Age group, ≥65	0.092	0.034	0.147	0.025	2.284	1.677
Race, White	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)
Race, American Indian or Alaska Native	0.099	0.013	0.190	0.040	2.377	1.402
Race, Asian	0.025	−0.013	0.063	0.017	1.456	1.000
Race, Black or African American	−0.016	−0.060	0.026	0.019	1.338	1.000
Race, multiple-race	−0.030	−0.081	0.027	0.024	1.518	1.000
Race, Native Hawaiian or Other Pacific Islander	−0.157	−0.520	0.217	0.164	3.234	1.000
Race, other	0.049	−0.042	0.132	0.039	1.748	1.000
Race, prefer not to say	0.068	−0.026	0.165	0.042	1.980	1.000
Hispanic ethnicity, no	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)
Hispanic ethnicity, prefer not to say	0.013	−0.064	0.092	0.035	1.296	1.000
Hispanic ethnicity, yes	−0.043	−0.081	0.001	0.018	1.676	1.216
Marital status, single	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)
Marital status, divorced	−0.008	−0.045	0.030	0.017	1.220	1.000
Marital status, married	−0.044	−0.072	−0.017	0.012	1.688	1.399
Marital status, prefer not to say	0.018	−0.097	0.117	0.048	1.365	1.000
Marital status, separated	−0.020	−0.145	0.098	0.054	1.392	1.000
Marital status, widowed	0.001	−0.057	0.062	0.026	1.069	1.000
Annual income, less than $20,000	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)
Annual income, $20,000 to $34,999	0.021	−0.020	0.064	0.019	1.405	1.000
Annual income, $35,000 to $49,999	0.024	−0.017	0.066	0.018	1.443	1.000
Annual income, $50,000 to $74,999	0.065	0.031	0.105	0.017	1.943	1.540
Annual income, $75,000 to $99,999	0.058	0.017	0.102	0.019	1.857	1.403
Annual income, $100,000 to $149,999	0.072	0.033	0.115	0.018	2.029	1.601
Annual income, over $150,000	0.115	0.076	0.162	0.019	2.597	2.102
Education, less than high school degree	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)
Education, high school degree or equivalent (e.g., GED)	0.042	−0.082	0.180	0.058	1.664	1.000
Education, some college but no degree	0.026	−0.097	0.165	0.058	1.469	1.000
Education, associate degree	0.041	−0.088	0.175	0.059	1.652	1.000
Education, bachelor degree	0.014	−0.108	0.149	0.057	1.311	1.000
Education, graduate degree	0.024	−0.098	0.160	0.058	1.443	1.000
Live alone	−0.035	−0.062	−0.007	0.012	1.579	1.275
Experienced COVID-19-like symptoms not serious enough to require hospitalization	−0.023	−0.055	0.013	0.015	1.431	1.000
Has a family member diagnosed with COVID-19	−0.080	−0.145	−0.023	0.027	2.130	1.483
Knows someone with a COVID-19 diagnosis	−0.005	−0.033	0.020	0.012	1.167	1.000
Fear of COVID-19's impact on health (1–10 scale)	−0.010	−0.013	−0.006	0.002	1.252	1.187
Fear of COVID-19's impact on finances (1–10 scale)	−0.002	−0.005	0.002	0.002	1.100	1.000
Arthritis	−0.115	−0.151	−0.077	0.017	2.597	2.152
Diabetes	−0.081	−0.126	−0.036	0.020	2.142	1.663
Depression	−0.122	−0.147	−0.097	0.011	2.696	2.397
Fear of COVID-19's impact on health (1–10 scale) * stroke	−0.034	−0.062	−0.008	0.012	1.567	1.260
BMI category, underweight * California	−0.263	−0.415	−0.109	0.068	5.375	2.813

Abbreviations: OLS ordinary least squares, CI confidence interval, CL confidence limit, BMI body mass index, COVID-19 Coronavirus disease 2019
**The coefficients given by this (post-lasso) OLS regression were bootstrapped to estimate standard errors, computed as the standard deviation of the bootstrap replicates. The standard errors were then used to construct Bonferroni-corrected normal-theory confidence intervals for the regression coefficients. In this table, we report the median bootstrap estimates as the model point estimates alongside the normal-theory bootstrap intervals*

compared to being single. Annual income levels ≥$35,000 were associated with significant increases in utility compared to annual incomes less than $20,000. Living alone, experiencing COVID-19-like symptoms not requiring hospitalization, and having a family member diagnosed with COVID-19 (n=187) were significantly associated with lower utility. Self-reported fear of COVID-19's impact on personal health (1–10 scale) was negatively and significantly correlated with utility.

Table 4 displays the post-lasso OLS regression median bootstrap estimates, bootstrap standard errors, bootstrap confidence intervals, and corresponding E-values. Estimates for predictors appearing in both the standard OLS and post-lasso OLS are largely similar. All additional predictors selected by

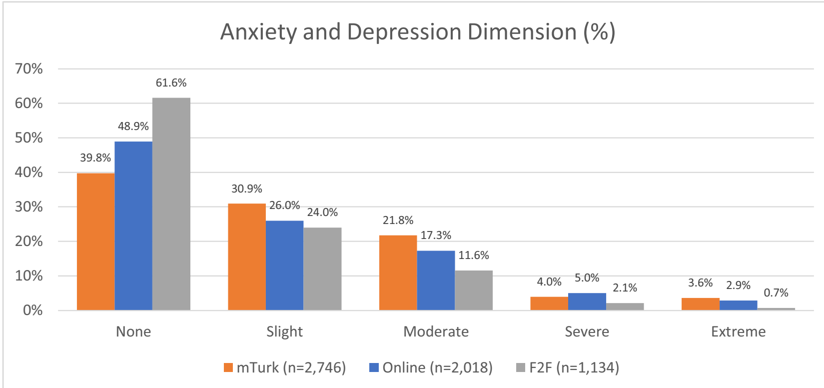

Figure 1 Anxiety and depression dimension. Percentage of individuals reporting none, slight, moderate, severe, and extreme problems with anxiety and depression by cohort. The during-pandemic cohort reports more problems than either online or face-to-face norms.

lasso—arthritis (*n*=244), diabetes (*n*=181), self-reported depression (*n*=541), stroke (*n*=28) interacted with fear of COVID-19's impact on health (1–10 scale), and underweight BMI (*n*=120) interacted with residing in California (*n*=274)—are significantly associated with lower utility. As with gender, the significant interaction between underweight BMI and California residence is driven mainly by self-reported diagnosis of anxiety/depression, which is distinct from the EQ-5D question on anxiety/depression (Supplemental Figure 2).

Results of the *F*-test indicate the additional coefficients estimated by the post-lasso OLS significantly improve the model's ability to predict EQ-5D utility (see Technical Appendix). Based on the estimated variance-covariance matrix from the bootstrap estimates, we are confident that normal approximation for the coefficients is robust and inference is normal (Supplemental Table 1, Supplemental Figure 1).[33]

Post-lasso OLS estimates for annual income over $150,000, arthritis, self-reported depression, and underweight BMI interacted with residing in California are most robust against bias from an unobserved confounder, all with *E*-value confidence limits $\geq$2.[32] Relatively strong unmeasured confounding (RR$\geq$2.9) would be required to attenuate modeled effects.

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 5).

DISCUSSION

HRQoL has decreased during COVID-19 compared to US population norms, especially for those 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 have 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. These findings are similar to those using the EQ-5D-5L in Germany, which found members of the general public experienced worse HRQoL, particularly if they reported fear of COVID-19 or had a history of chronic illness and anxiety/depression[19]; similar EQ-5D findings in China also showed that lower income and unemployment decreased HRQoL.[22, 34]

Although HRQoL was higher than population norms among those >35 years, this may reflect a healthier, more highly educated sample compared to the US general population 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.

We employed traditional OLS regression alongside a lasso-selected bootstrapped linear model to identify significant associations between respondent characteristics and HRQoL. As demonstrated by the *F*-test, the post-lasso model significantly improved fit over the standard model, indicating that lasso provides a more sophisticated method for testing specifications in high dimensional settings vs. stepwise selection, with the additional benefit of decreasing variance of estimates

Table 5 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*

compared to the standard model. We also calculated *E*-values for all point estimates and found that relatively strong unmeasured confounding (RR≥2.9) would be required to attenuate all lasso-selected effects. For additional details, refer to the Technical Appendix.

We compared our results to a similar multivariable analysis of sociodemographic and behavioral predictors of EQ-5D utility based on a 2008 general population survey in England.[35] While most predictors examined were included in our model, they also reported estimates for additional confounders such as alcohol consumption, smoking, fruit and vegetable intake, and physical activity. Among these, only being physically inactive has an effect size upper bound of RR>2.5. Given this, and the fact that we demonstrate good covariate control in our model, our estimates are robust to unobserved confounders like alcohol, smoking, diet, and exercise. Since the UK study is based on an EQ-5D-5L survey of the general population (much like ours) in England (culturally similar to the USA) 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, which has been shown to have mixed external validity on context.[28, 36–39] Nonetheless, we believe our results overestimate HRQoL 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%.[40, 41] 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

COVID-19's impact on American HRQoL varies by age group, with the largest negative impact on young adults aged 18–24 years. These results suggest that policies such as universal lockdowns, without risk-assessment by age or demographic characteristics, may have been implemented at the expense of the mental well-being of younger adults whose health outcomes have been discounted relative to older adults >35 years based on policy initiatives to date; under normal circumstances, this group (and particularly more elderly individuals) are more likely to stay home and self-isolate compared to younger adults; thus, lockdowns may have had a lower impact on this group than on younger adults, who are generally more mobile in their normal daily activities. It is important to consider the long-term implications of policies implemented during epidemics that may disproportionately impact the health and well-being of subgroups of the population, such as young adults in the USA during the COVID-19 pandemic.

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Declarations:

Conflict of Interest: *ASP reports that he is a member of the EuroQol group and 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. FX and NYG are also members of the EuroQol group. NKZ and SAC report grants from EuroQol Foundation during the conduct of the study. All other authors report no other conflicts of interest.*

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