**Data and Methods – Michele Giunti**

**Data Used**

*General Social Survey*

The dataset used in this analysis was pulled from the General Social Survey (GSS) website, a nationally representative survey of the attitudes and behaviors of adults (18 and over) in the United States. The survey is taken by the National Opinion Research Center (NORC) every one to two years, with cumulative cross-sectional datasets available from the year 1972 to 2021[[1]](#footnote-1). The specific data employed will be the 2016-2020 Panel (Davern, Bautista., Freese, Morgan, & Smith, 2022) updated in April 2022, which sampled 6,200 housing units in 2016, with a final tally of 2,867 completed interviews, and 5,200 housing units in 2018, with a final tally of 2,348. The 2020 respondents were obtained from a full sample of the 2018 wave, and a random subsample of 2,146 (74.85%) from the 2016 wave. The total number of included observations was 5,215, however, accounting for attrition and respondent non-answers[[2]](#footnote-2), the total number of functional observations was 1,823 (34.95%). For the purpose of tracking the same respondents across waves, only those that participated in the 2018 survey were considered, reducing the final observation number to 1,014.

*American National Elections Survey*

The American National Elections Survey (ANES) is one of the oldest continuous series of survey data of electoral behavior and general attitudes in the United States. The surveys are taken before and after presidential elections and national congressional elections by both the Institute of Social Research at the University of Michigan and the Institute for Research in the Social Sciences at Stanford University; latest efforts have included experts from Duke University and the University of Texas at Austin.

The 2016-2020 panel collaborated with the American National Elections Survey by offering to all respondents who completed the 2020 wave, and were U.S. citizens at the time, an additional post-election interview. All eligible 1,734 respondents were invited, with the final retention rate being 1,164 (67%). Merging the datasets by respondent ID (yearid) and restricting the observations to those also present in the 2018 sample, resulted in a final observation count of 635. For the purpose of the paper, the use of these cross-referenced ANES observations will be preferred, but the main focus will remain on the GSS sample.

**Tabulation of uscitzn\_2**

|  |  |  |  |
| --- | --- | --- | --- |
| is r us citizen | Freq. | Percent | Cum. |
| a u.s. citizen | 956 | 95.12 | 95.12 |
| not a u.s. citizen | 40 | 3.98 | 99.10 |
| a u.s. citizen born in puerto rico, the u.s. virgin islands, or the northern marianas islands (if volunteered) | 5 | 0.50 | 99.60 |
| born outside of the u.s. to parents who were u.s. citizens at that time (if volunteered) | 4 | 0.40 | 100.00 |
| Total | 1005 | 100.00 |  |
|  | | | |

*Weights*

Both the GSS and the ANES offer a selection of weights to account for non-response in the stratified sample areas. The first survey provides a standard variance stratum (vstrat) and a variance primary sampling unit (vpsu), with a each wave either accounting for sub-sampling of nonrespondents and number of adults in the household (wtssall) or the area non-response adjustment based on the stratified units (National Frame Areas; wtssnr). The codebook recommends the use of the wtssnr. On the other hand, the joint ANES file offers both standard variance clusters (V20001xc) and variance stratum (V20001xd) a GSS post-election weight for the GSS cases alone (V200017b), a combined ANES-GSS post-election weight with the mixed video sample groups (V200018b), and a similar weight without mixed video sample groups (V200019b). Considering the adaptations made to the ANES collaboration, it is likely that the latter survey set weights will be used.

**Model Specification and Testing**

The effect of loneliness on our variables of interest will be measured at a high to low categorical scale, expecting increased effects on the extreme ends of the distribution, while the majority near the mean either does not experience significant correlations or sees relationships different from the tails. As such, the models used will be either an Ordered Logit Fixed Effects model or a Random Effects model, with the dependent variable being coded as to distinguish the three distinct categories (High, Medium, Low).

*Fixed Effects vs. Random Effects*

The choice of Fixed Effects or Random Effects arises from the presence of similar observations across waves, which allows us to account for time-invariant individual characteristics without the need for further controls. In the case of the Fixed Effects, the individual heterogeneity is included in the intercept and allowed to be correlated with other regressors, while the Random Effects model places the assumption that the individual effect is not correlated with the regressors, estimating the error variance (Park, 2011).

Fixed Effects:

Random Effects:

Both where

Given that we assume that the observations are unique from each other, and we want to draw conclusions from the differences among each individual, the Within-Effect Fixed Effects model is more appropriate, especially since we have a limited number of respondents and time periods to analyze (Yang & Land, 2008). Further, the limitation placed on the use of only two years of data could make it so that using a First Difference (FD) model would be better: . However, FD assumes that the idiosyncratic error term is serially uncorrelated with each period, which can be problematic with vulnerable population analysis during the COVID-19 period (Especially seniors; Fawcett & Karastoyanova, 2022). As such, the Hausman test will be performed to determine if either the RE or FE models yield more consistent and unbiased estimates.

*Estimation and Causality*

Considering the use of the Ordered Logit model in a Fixed Effects contest, the problem of estimation arises due to the larger standard errors and the absence of time-constant predictor estimates (Vaisey & Miles, 2017). Still, we trade this for the possibility of countering selection effects from the time-constant fixed effect (*u*) on the independent treatment variable (*x*), assuming that all cases within the model have a similar trajectory of change for the dependent variable (*y*). Unfortunately, it also makes causal inference difficult to determine, unless a lagged model is implemented; the latter might skew our estimates if the lag does not match the real-world causal lag.

While still maintaining unique categorization, and the difference between extremes and middle values, estimation of the Ordered Logit model can be performed through a variety of methods that employ the reduction of the model to a binary estimation without loss of information: Chamberlain’s CML estimator, Das and van Soest’s estimator, the Ferrer-i-Carbonell and Frijters estimator, and The “Blow Up and Cluster” (BUC; Baetschmann, G., Staub, K. E., & Winkelmann, 2015). The latter seems to be more efficient in smaller sample contexts (Riedl & Geishecker, 2014), and a community contribution STATA command package described by Baetschmann, Ballantyne, Staub and Winkelman (2020) – *feologit –* allows for its easy use within the statistical program, with the option of a hybrid BUC-τ if we assume constant thresholds across individuals.

**Dependent Variables**

All dependent variables were included in both the 2018 and 2020 waves, assuring some level of stability across respondents. Three categories of variables were selected to address the three aspects of our research questions: Health, Happiness, and Social Cohesion. Each variable, including the independent variables, were coded as \_1b to indicate data collected in 2018, and \_2 to indicate data collected in 2020; for the purpose of clarity, the suffixes will be omitted in the variable description.

*Health*

Self-Perceived *health* was measured through a 4-point scale answering the following: “Would you say your own health, in general, is excellent, good, fair, or poor?” The scale adopted the Excellent, Good, Fair, Poor distinction, but the “Poor” category will be collapsed into the “Fair” category due to the limited number of observations. A Shapiro-Wilk test on the non-collapsed variables revealed that the distribution was indeed marginally non-normal (z = 1.580, p = 0.05701), although the 2018 wave showed the opposite (z = 2.123, p = 0.01690).

**Tabulation of health\_2**

|  |  |  |  |
| --- | --- | --- | --- |
| condition of health | Freq. | Percent | Cum. |
| excellent | 132 | 19.50 | 19.50 |
| good | 357 | 52.73 | 72.23 |
| fair | 161 | 23.78 | 96.01 |
| poor | 27 | 3.99 | 100.00 |
| Total | 677 | 100.00 |  |
|  | | | |

**Tabulation of health\_1b**

|  |  |  |  |
| --- | --- | --- | --- |
| condition of health | Freq. | Percent | Cum. |
| excellent | 160 | 23.63 | 23.63 |
| good | 341 | 50.37 | 74.00 |
| fair | 146 | 21.57 | 95.57 |
| poor | 30 | 4.43 | 100.00 |
| Total | 677 | 100.00 |  |
|  | | | |

*Happiness*

Self-Perceived *happiness* was measured through a 3-point scale answering the following: “Taken all together, how would you say things are these days--would you say that you are very happy, pretty happy, or not too happy?” The scale adopted the Very Happy, Pretty Happy, and Not Too Happy distinction, which was not modified for easier categorization.

**Tabulation of happy\_1b**

|  |  |  |  |
| --- | --- | --- | --- |
| general happiness | Freq. | Percent | Cum. |
| very happy | 311 | 30.70 | 30.70 |
| pretty happy | 563 | 55.58 | 86.28 |
| not too happy | 139 | 13.72 | 100.00 |
| Total | 1013 | 100.00 |  |

**Tabulation of happy\_2**

|  |  |  |  |
| --- | --- | --- | --- |
| general happiness | Freq. | Percent | Cum. |
| very happy | 197 | 19.49 | 19.49 |
| pretty happy | 516 | 51.04 | 70.52 |
| not too happy | 298 | 29.48 | 100.00 |
| Total | 1011 | 100.00 |  |

*Social Cohesion*

Measures for social cohesion were separated into three distinct dummies with three distinct set of responses: *trust* (“Generally speaking, would you say that most people can be trusted or that you can't be too careful when dealing with others?”), *fair* (“Do you think most people would try to take advantage of you if they got a chance, or would they try to be fair?“), and *helpful* (Would you say that most of the time people try to be helpful, or that they are mostly just looking out for themselves?”). Certain authors like Mewes, Fairbrother, Giordano, Wu, & Wilkes (2021) took the mean of the three variables to obtain a generalized dependent scale going from 0 to 1, with 0 indicating negative connotations of trust, while numbers closer to 1 pointed at higher trust and social cohesion. On the other hand, others like Glanville, Andersson, and Paxton (2013) created a composite index of latent generalized trust, which was based on a previous analysis by Paxton (1999) confirming the stability of these parameters when aggregated together[[3]](#footnote-3).

While it is not yet clear what methodology would be best to standardize the three measures, the parameters will be standardized into a 0 and 1 dichotomy, collapsing the “Depends” answer common of all three into the 0 level (Carl & Billari, 2014). This is justified by the low cell value of the category, and the perceived negative connotation of doubt when inquired on the reliability of other people.

**Tabulation of fair\_2**

|  |  |  |  |
| --- | --- | --- | --- |
| people fair or try to take advantage | Freq. | Percent | Cum. |
| would take advantage of you | 292 | 43.91 | 43.91 |
| would try to be fair | 359 | 53.98 | 97.89 |
| depends | 14 | 2.11 | 100.00 |
| Total | 665 | 100.00 |  |
|  | | | |

**Tabulation of fair\_1b**

|  |  |  |  |
| --- | --- | --- | --- |
| people fair or try to take advantage | Freq. | Percent | Cum. |
| would take advantage of you | 263 | 39.20 | 39.20 |
| would try to be fair | 367 | 54.69 | 93.89 |
| depends | 41 | 6.11 | 100.00 |
| Total | 671 | 100.00 |  |
|  | | | |

**Tabulation of trust\_2**

|  |  |  |  |
| --- | --- | --- | --- |
| can people be trusted | Freq. | Percent | Cum. |
| can't trust | 242 | 36.07 | 36.07 |
| can't be too careful | 419 | 62.44 | 98.51 |
| depends | 10 | 1.49 | 100.00 |
| Total | 671 | 100.00 |  |
|  | | | |

**Tabulation of trust\_1b**

|  |  |  |  |
| --- | --- | --- | --- |
| can people be trusted | Freq. | Percent | Cum. |
| can't trust | 236 | 35.07 | 35.07 |
| can't be too careful | 403 | 59.88 | 94.95 |
| depends | 34 | 5.05 | 100.00 |
| Total | 673 | 100.00 |  |
|  | | | |

**Tabulation of helpful\_2**

|  |  |  |  |
| --- | --- | --- | --- |
| people helpful or looking out for selves | Freq. | Percent | Cum. |
| try to be helpful | 381 | 56.61 | 56.61 |
| looking out for themselves | 281 | 41.75 | 98.37 |
| depends | 11 | 1.63 | 100.00 |
| Total | 673 | 100.00 |  |
|  | | | |

**Tabulation of helpful\_1b**

|  |  |  |  |
| --- | --- | --- | --- |
| people helpful or looking out for selves | Freq. | Percent | Cum. |
| try to be helpful | 335 | 49.70 | 49.70 |
| looking out for themselves | 286 | 42.43 | 92.14 |
| depends | 53 | 7.86 | 100.00 |
| Total | 674 | 100.00 |  |
|  | | | |

**Independent Variables**

The calculation of the independent variables will vary across years, as not all elements of the 2018 questionnaire were included in the 2020 questionnaire. However, the wording of differentiated variables was similar across the two waves, and the ANES addendum helps complement the missing aspects of certain omitted variables. The naming of the variables will not include their suffixes \_1b and \_2, but will be specified explicitly by year.

*Loneliness*

Measures of loneliness were identified by the *lonely3* parameter (“How often in the past 4 weeks have you felt that you are left out?”) in 2018, and by the *lonely1* and *lonely2* parameters (“How often in the past 4 weeks have you felt that you lack companionship?”; “How often in the past 4 weeks have you felt that you are isolated from others?”) in 2020. While *lonely3* seems to directly capture the aspect of emotional loneliness we want to express (Prohaska et al. 2020), *lonely1* and *lonely2* seem to distinguish emotional loneliness with physical loneliness, the latter as a consequence of concrete restrictions of interaction (Holt-Lunstad & Steptoe, 2022). The variable *conwkday* in 2018 measures the number of people a respondent contacts in a typical weekday (“Please indicate about how many people do you have contact with on a typical weekday irrespective of whether you know them or not. Include anyone you chat with, talk to, or text, either face-to-face, by phone, internet or any other communication device.”), which can be used as a way to pair the lonely3 variable in 2018. As such we would obtain two distinguished measures of both emotional and physical loneliness that would determine which is more important in the variation of health, happiness, and trust (Lee & Lee, 2010; Vacchiano & Bolano, 2021). Previous literature predicts that the former will have a lesser, though still negative, effect on the three if we take into account a person’s preferred method of communication (Digital or Physical; Steafnone, Huang, & Lackaff, 2011)

*Communication Methods*

Measures of communication will be determined by the variables *conf2f* (“About how many of these people do you see face-to-face on a typical weekday?”) and *intcntct* (“Think now of your contact with all of your family members and close friends. How much of it is through text messages, mobile phones, or other communication devices that use the internet?), which consider respectively the number of physical interactions and digital interactions a person faces. The main limitation of these two variables is that they are exclusive to the 2018 wave, and their wording doesn’t concurrently specify the time frame by which this interaction takes place. While the fixed effects model should compensate for the first limitation, the difference in content might need to be checked for misspecification. Further, the ANES addendum contains a set of variables V202541a-b-c-d-f, which track number of visits to Facebook, Twitter, Instagram, Reddit and Snapchat respectively, allowing some degree of follow-up to online communication patterns. We expect, however, that the effect of social digital interactions will be driven by the level of social real-life interactions (Filiposka, Gajduk, Dimitrova, & Kocarev, 2017), and that placing online communication frequency as a mediator across the relationship with political participation will damper the positive effect of the latter on Health, Happiness, and Social Cohesion.

*Social Contact*

The General Social Survey contains four different measures of social interaction: *socbar, socfrend, socommun,* and *socrel*, respectively asking how often an individual spends his social evening at the bar, with friends, with neighbors or with relatives. A considerable number of papers (Mewes, Fairbrother, Giordano, Wu & Wilkes, 2021; Zhang & Xiang, 2019; Bianchi & Vohs, 2016) have adopted Glanville’s (2013) transformation of the four variables, which where previously coded in a 1 to 7 scale (going from “Almost Daily” to “Never”). This consists in turning a combination of the four into a numeric indication of days per year, with “Almost Daily” being assigned 300, “Once a year” 1, “Never” 0, and “Several” being 4 (thus “Several Times a Week is 208 or 4x52, “Several Times a Month” is 48 or 4x12, and “Several Times a Year is 4 or 4x1). The presence of all variables in both wave ballots allows for constant tracking of their effect, which is expected to be positive on all the dependent variables. People at different extremes of this factor variable will be more likely to experience the negative effects of loneliness and online interactions on our three dependent variables (Kim, 2017; Pittman, 2018), while the positive effect among people within the middle of the distribution has been shown to be typically positive and still significant (Chopik, 2016).

*Political Participation*

Differing from previous research, the behavioral aspect of social trust is placed upon a person’s willingness to participate in political and community activities. This is not the same as spending time with friends and acquaintances, but rather shows a level of connectedness with the individual’s surroundings that is strong enough to warrant collaboration and participation. Questions that tracked a person’s political participation in 2018 were included in the *partlsc*, *parpart* and *partvol* variables (“In the past 12 months, how often, if at all, have you taken part in the activities? Of groups or associations for leisure, sports or culture?”, In the past 12 months, how often, if at all, have you taken part in the activities? Of political parties, political groups or political associations?” and “In the past 12 months, how often, if at all, have you taken part in the activities? Of charitable or religious organizations that do voluntary work?”). Each of these are coded on a 5-point scale, going from “Once a Week or More” to “Never”. In 2020, the ANES annex contained 9 different questions tracking political participation, not including direct contact with governmental institutions. These asked for an individual’s participation in political arguments, marches, religious organizations, money donations, online discussions, community problem-solving, school management, and volunteering, with each being coded as 1 “Have done this in the past 12 months” and 2 “Have not done this in the past 12 months”.

In a similar fashion as the social cohesion dependent variable, each group will be collapsed into binary dummies and indexed together to form a singular score. Political participation is expected to have a positive effect on all three dependent variables, but its effect will be reduced by the higher levels of online communication (Moy, Manosevitch, Stamm, & Dunsmore, 2005), but only at either very high or very low levels of social contact.

**Controls**

While the FE model does deal with time-invariant variable effects, certain time-variant aspects of a person’s daily life can indirectly affect the role that online communication has in health (age, technology use), happiness (income, marriage happiness), and social cohesion (religious attendance, cohabitation status).

*Marriage Happiness and Cohabitation Status*

Marriage happiness has been shown to shield people from stressors of mental health. To this degree, DeMaris (2020) finds this relationship to be significant, also providing a length of studies backing his results, and if we further consider the elevated importance of a partner’s intimate relationship within the perception of social connectedness (Prohaska et al., 2020), marriage can severely skew our estimation. In addition, we place it as a time variant control due to the consistent high number of divorces and the declining number of marriages within the U.S. (National Vital Statistics System, 2022), with *marital* being a consistent variable in presence across waves. Still, considering that the physical presence of the partner itself is further important to the overall effect of the intimate connection, *marcohab*, which tracks if a person is both married *and* living with their spouse, will most likely be used as an alternative to *marital*.

*Income*

A person’s income can come to affect its daily internet use, as people in the poorer tracts might find it more difficult to sustain a good internet connection (Powell, Bryne, & Dailey, 2010). Apart from this basic distinction, analysis sustained on GSS data has already shown the relationship between lower happiness and less fortunate socio-economic groups (Hout, 2016), and Hastings (2018) had also previously found that there is some degree of relationship between trust and income inequality within states. Further, it is common for other papers analyzing panel data to take the log transformation of income as a measure of control (Carl & Billari, 2014; Zhang & Xiang, 2019), and to use family income rather than respondent income as it tracks occupational earnings rather than total earnings. Mewes, Fairbrother, Giordano, Wu, and Wilkes (2021) further divided inflation adjusted income (*realinc*) with the square root of the number of household members, to account for individual disposable income. However, considering that *hompop* (tracking number of persons in the household) does not have a corresponding 2020 counterpart, we would have to assume that household size did not change between waves.

*Religious Attendance*

Attendance to religious events allows people to feel more connected to one another and gives them additional reasons to get together and avoid isolation (Whitehead & Stroope, 2015). Secular analysis by Hastings (2016) further proves this point by indicating that, while quality of friendship could not be verified, both spiritual and non-spiritual persons benefit by engaging in religious activities. Other papers further point at the role of religious participation on an increased sense of wellbeing, connectedness and social participation (Dunbar, 2021; Lewis; MacGregor, & Putnam, 2013), although the relationship with life satisfaction requires a stronger spiritual connection with the group (Lim & Putnam, 2010). We assume, nevertheless , that religiosity is time-invariant within our sample selection, and we only use *attend* as a tracker of religious service attendance (“How often do you attend religious services?).

*Technology Use*

Inclusion of technology use in our model has to be twofold: firstly, we would need to take into account the change in actual hours spent on the internet; the timeframe including the advent and consequences of the pandemic obliges a necessary understanding of the need for digital interactions within contexts of social isolation. Quite so, as discussed before, private investigations in the change in patterns of internet use revealed a consistent increase throughout 2020 and 2021 (McClain, Vogels, Perrin, Sechopoulos, & Rainie, 2021). To this point, a simple inclusion of *wwwhr* (“Not counting e-mail, about how many minutes or hours per week do you use the Web? (Include time you spend visiting regular web sites and time spent using interactive Internet services like chat rooms, Usenet groups, discussion forums, bulletin boards, and the like.)”), would suffice to control for this change. However, we should also take into account the role that the digital world has in the individual’s life, as people whose work directly involves heavy internet use might skew simple tracking of hours spent on the web. As such, *occ10,* which uses the census’ occupational coding,will be adapted into an *occtech* dummy that places individuals whose job revolves around the web at 1 and others at 0.

*Age*

While it is true that a person’s age may affect their rate of technological use, the role of age in our analysis connects more with its mediation between technology use and loneliness. The GlobalWebIndex report (Mander, Buckle, & Moran, 2020) indicates that baby boomers and older generations have begun to diversify their digital life, and increase their non-face to face connectiveness with considerable reductions in measures of loneliness (Luchetti et al., 2020). Within the GSS, age is a continuous variable, but, considering that we know this positive effect starts at the age of retirement, a transformation to a categorical variable, with a clearly defined “65 and over” level, will be enough to account for it.

**Addressing Missingness**

Panel data is unfortunately prone to missingness due to attrition or methodological changes across panel years. In fact, even in the 2016-2020 panel, though wording remains relatively identical across included variables, certain questions are either omitted or substituted from the 2016 and 2018 waves to the 2020 wave. In addition, non-response negatively affects the explanatory power of certain variables, and imputation is necessary to reestablish the usefulness of the data. The 2016-2020 panel was selected for its relative stability in questionnaire variation, and a previous analysis by Smith (2010) on the patterns of missingness within the 2006-2008 survey panel indicates that more complex questions tend to attract higher percentages of missingness, confirmed by the completeness of demographic variables such as race (99.51%) and sex (99.31%) in our own dataset.

*Full Information Maximum Likelihood*

As we come to examine pattern distributions across waves, listwise deletion or pairwise deletion of missing observations would reduce our sample number to unrepresentative levels, further necessitating the assumption of Missing Completely At Random and Missing At Random to be enacted(Enders & Bandalos, 2001). This issue becomes more glaring if we consider that questions varied in presence rather than content across waves, and we might find that aggressive imputation might delete fundamental explanatory variables from the data. As such, we utilize Full Information Maximum Likelihood to estimate the likelihood function of each observation using the data available (Larsen, 2011; Cham, Reshetnyak, Rosenfeld & Breitbart, 2017). The method has been proven to produce unbiased estimates through correct standard errors, and is particularly useful for lower N samples such as ours, as demonstrated by Glanville et al. (2013).[[4]](#footnote-4)

**First Findings and Descriptive Statistics**

***2020***



***2018***

The data shows that perceived health was relatively stable throughout the two waves, although it tended to shift towards “poor” between the 46- to 64-year-old individuals, just before the retirement age. On the other hand, happiness seems to have severely decreased across all ages (going from “very happy” to “not to happy”, although the number of those that claimed to be “pretty happy” seemed to remain almost constant.

***2020***



***2018***



When it comes to social cohesion, perception of fairness increased among younger people (23.56% to 33.33%), but decreased across all the older generations. On the other hand, helpfulness perception saw greater change across people 46 and over (51.83% to 60.65% and 61.78% to 74.14%). Finally, levels of trust increased for all age groups, except for the 26 to 45 category, which saw a decrease of almost 6%.

***2020***



***2018***



As far as measures of loneliness, although a direct comparison is not currently feasible due to a lack of transformation and model adaptation, we can see that loneliness did generally increase between 2018 and 2020, with older individuals being hit the most in the context of companionship (emotional loneliness), while younger age groups suffered more on the social isolation aspect (physical loneliness).

***2020***



***2018***



A more summary description has to be given on technology use, as per the limitations of the initial analysis. As expected, digital presence was higher among younger generations, but there was still some degree of use among older people, as they populated the “most of it category” (46.95% of 46 to 64, and 47.11% of 65+). The pattern remained similar in 2020 when analyzing social media use, and we can distinguish sites more popular with younger generations (Reddit and Snapchat), with adults (Instagram), and with seniors (Facebook and Twitter).

**Tabulation of conf2f\_1b by intcntct\_1b**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| how many people r sees face to face | how much of r's communication is via text, mobile phone, or internet | | | |
| all or almost all of it | most of it | about half of it | Total |
| all or almost all of them | 33 | 34 | 9 | 76 |
|  | 43.42 | 44.74 | 11.84 | 100.00 |
| most of them | 86 | 47 | 8 | 141 |
|  | 60.99 | 33.33 | 5.67 | 100.00 |
| about half of them | 57 | 46 | 3 | 106 |
|  | 53.77 | 43.40 | 2.83 | 100.00 |
| some of them | 76 | 57 | 12 | 145 |
|  | 52.41 | 39.31 | 8.28 | 100.00 |
| none or almost none of them | 23 | 9 | 8 | 40 |
|  | 57.50 | 22.50 | 20.00 | 100.00 |
| Total | 275 | 193 | 40 | 508 |
|  | 54.13 | 37.99 | 7.87 | 100.00 |
| Pearson Chi2 = 21.44 Prob = 0.0061 | | | | |

First row has *frequencies* and second row has *row percentages*

Delving deeper in the 2018 patterns of technology use, it can be inferred that face-to-face communication behaviors are evenly distributed across the mean, while internet communication was highest with people who did not engage in many social interactions (“Most of them” 60.99% and “None or almost none of them” 57.50%), while it was lower at both extremes than among people who had adequate levels of social interaction (“About half of them” and “Some of them”). From the simple Pearson’s chi2 correlation test, we can see that the relationship between the two is highly significant (Chi2 = 21.44, p = .0061).

A final analysis was done on the simple correlations between the three independent variables across both waves, and the loneliness variables. The results indicated that all relationships were statistically significant at the 5% level of significance, but the trust and helpful sub variables of social cohesion did not hold a statistically significant relationship with either *lonely1, lonely2* in 2020, while the *fair* sub variable’s relationship with loneliness was significantly in both years.

|  |  |  |  |
| --- | --- | --- | --- |
|  | Lonely3\_1b | Lonely1\_2 | Lonely2\_2 |
| Happy\_1b | 55.38658 |  |  |
| p < .001 |  |  |
| Happy\_2 |  | 121.7336 | 103.5526 |
|  | p < .001 | p < .001 |
| Health\_1b | 10.269 |  |  |
| p = .036 |  |  |
| Health\_2 |  | 35.629 | 27.3782 |
|  | p < .001 | P < .001 |
| Fair\_1b | 18.9323 |  |  |
| p < .001 |  |  |
| Fair\_2 |  | 6.4127 | 8.7698 |
|  | P < .041 | p < .012 |
| Trust\_1b | 9.2255 |  |  |
| P = .010 |  |  |
| Trust\_2 |  | 1.283 | 3.0774 |
|  | p < .526 | p < .215 |
| Helpful\_1b | 12.6275 |  |  |
| p = .002 |  |  |
| Helpful\_2 |  | 0.8464 | 3.5434 |
|  | p < .655 | p < .170 |

**References**

American National Election Studies. (2022). *ANES-GSS 2020 Joint Study*[dataset and documentation]. April 8, 2022 version. [www.electionstudies.org](http://www.electionstudies.org/)

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1. Information obtained from the GSS website: <https://gss.norc.org/About-The-GSS> [↑](#footnote-ref-1)
2. Panstat tracks whether a respondent was selected and reinterviewed (1 = Selected, Eligible, and Re-Interviewed, 2 = Not Selected, 3 = Selected, but not re-interviewed, 4 = Selected, but not eligible and not re-interviewed because R was deceased, 5 = Selected, but not eligible and not re-interviewed because R was permanently incapacitated, outside the U.S., or otherwise out of scope) [↑](#footnote-ref-2)
3. Paxton’s research also looked into elements of trust in institutions and of social connections, which relates back to the use of social participation as an independent variable (Figure 1 and Figure 2) [↑](#footnote-ref-3)
4. Two STATA commands exist to produce this method: xtdpdml by Williams, Allison and Moral-Benito (2018) and xtdpdqml by Kripfganz (2016), which instead uses quasi-maximum likelihood estimation for shorter T panels. [↑](#footnote-ref-4)