**Screens and Faces: A Fixed Effects Model for Loneliness Wellness Effects**

**Across Face-to-Face Interactions and Online Communities**

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# **Abstract**

The information age has allowed people to stay connected with each regardless of physical distance, and it exposed vulnerable populations to heightened levels of support and care. However, opinion pools and surveys show that levels of loneliness have remained the same, and even occasionally increased, from one decade to the next. Considering this unexplained rise in perceived isolation, and its negative reported effect on health, happiness, and social cohesion, the role of virtual interaction within this relationship is examined through a parallel examination of pre and post pandemic survey responses, extracted from the General Social Survey and the American National Elections Study. Expected results will show the verified negative relationship between loneliness and the three determinants of wellness: health, happiness, and social cohesion, and verify if increased online connectedness paired with reduced face to face interaction contribute to a significant change in this relationship.

*Keywords:* Information age, loneliness, health, happiness, social cohesion, online connectedness

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# **Introduction**

With the rise the internet and the increasing evolution of online connectivity tools, physical distance has ceased to become a limitation to the maintenance of social relationships. In fact, many offline interactions, though initiated in real life, tend to be continued online, with occasional meetups interrupting the continuous stream of communication (Scott, Stuart, & Barber, 2021). In turn, this constant flow of sociability allows us to maintain a stable level of mental health, by reducing loneliness, and increases our potential for social support, by increasing social cohesion, health empowering behaviors, and resilience factors (Liu, Liu, Niu, & Longobardi, 2020; Kamalpour, Watson, & Buys, 2020). However, free interactivity does not imply empowering communication, as it still requires an active commitment to communicate between users, yet the possibility of isolation within this highly connected network is often dismissed as unlikely.

Catastrophes such as the pandemic reveal the limitations of both physical and digital tools of communication, as the limits imposed by quarantine, or any other interruption in the continuous flow of social interaction, come to affect both our psychological stability and our physical health. Following this, numerous studies have found that protracted isolation and low community trust may bring sleep disturbances, poor estimation of health, depression and high suicide risk (Hwang, Rabheru, & Peisah, 2020; Hämmig, 2019; Rauschenberg, Schick, Goetzl, Roehr, Riedel-Heller, Koppe, ... & Reininghaus. 2021). Furthermore, even among healthy individuals, the perceived effect of decreasing mental and physical health can bring about stress related illnesses, such as cardiovascular irregularities, dysfunctional health habits and resurgence of chronic illnesses (Kim, 2021; Mohnen, Groenewegen, & Völker, 2011).

In such case, the pandemic represented not only a health crisis, but also a mental health crisis; studies conducted by Harvard on a representative sample of 950 U.S. adults report that about 36% of these had felt lonely by late October 2020 (Weissbourd, Batanova, Lovison, & Torres, 2021). The worst effects are found at the ends of the age spectrum as young adults and students felt substantial decreases in the number of social needs being met and a rise in depression morbidity[[1]](#footnote-1) (Towner, Tomova, Ladensack, Chu, & Callaghan, 2022). On the other end, pooling from surveys pre and intra-pandemic, about 22% to 24%[[2]](#footnote-2) of the over 65 and up population felt lonely even before pandemic-related social isolation (Cudjoe, Roth, Szanton, Wolff, Boyd, & Thorpe Jr, 2020; DiJulio, Hamel, Muñana, & Brodie, 2018), leading to substantial rises in perceived isolation by 2020 and 2021. This can lead to cases such as those evidenced by a San Francisco social isolation study, which reported around 50% of a representative sample of 151 elderly being abandoned without any form of social support (Kotwal, Holt‐Lunstad, Newmark, Cenzer, Smith, Covinsky, ... & Perissinotto, 2021).

The rise of Information and Communications Technologies (ICT) like Zoom, WhatsApp, Facebook and Facetime allowed for some form of coping through this forced isolation, by reestablishing communicative relationships with friends, family, and colleagues, as well as by maintaining an information network connecting vulnerable individuals to the outside world (Lee, Malcein, & Kim. 2021, Mander, Buckle, & Moran, 2020). It is not uncommon for Online Communities (OC) to form under these circumstances, much in the way that physical communities act as buffers and resilience mechanism in situations of extreme duress (Bergstrand & Mayer, 2020, Li, Luo, Mu, Li., Ye, Zheng, Xu, Ding, Ling, Zhou, & Chen, 2021).

Accordingly, reports by the GlobalWebIndex and the Pew Research Center indicate that the growth of internet use was also met with a radical change in the way that we experience the web, with 40% of sampled U.S. adults[[3]](#footnote-3) reporting of having used digital technology in a different way since the pandemic (McClain, Vogels, Perrin, Sechopoulos, & Rainie, 2021). A trend which actually preceded forced social isolation, since online community participation had been growing since 2017 (From 72% to 76% in 2019, Reddit & GlobalWebIndex, 2019). Overall, the increased role of OCs in the U.S.’s system of social support might have been accompanied with a resurgence of hope and a decrease in overall loneliness, as the increase in social isolation and mental health mediators such as self-esteem, self-efficacy, and social support has been proven to be significantly associated with increased online communication (Fawcett & Karastoyanova, 2022; Kearns & Whitley, 2019).

Nevertheless, OCs operate differently from physical communities, as associations of proximity and need are substituted by associations of interest and commonality (Groenewegen & Moser, 2014), with online interactions being employed as an auxiliary rather than a surrogate of offline interactions (Scott, Stuart, & Barber, 2021; McCully, Lampe, Sarkar, Velasquez, & Sreevinasan, 2011). Yet, online communication has to exist in a space outside of offline interaction, and often the two act as complementary activities for individuals whose personal characteristics direct to prefer one over the other (Sessions, 2010; Turner, Grube, & Meyers, 2001). What is most worrisome about this phenomenon is the concurrent evolution of the void forming between community members as OCs evolved throughout the 21st century (Wellman, Boase, & Chen, 2002): though advanced connectivity allows for reduced social isolation and loneliness, the quality of the relationship itself is not equivalent to its offline counterpart, sacrificing cohesion, trust, and group identification (Lee & Lee, 2010; Cullen & Sommer, 2010). Further, while mental health might be improved through the reduction of loneliness, activities performed online might actually cancel out OCs’ mediating effect and reduce the quality standards of existing communities (Vacchiano & Bolano, 2021; Gil de Zúñiga & Valenzuela, 2011).

There is little discussion surrounding this multidimensional aspect of Online Communities on loneliness, mental health, and social cohesion, especially compared to studies concerning physical communities and their overall member effect. As such, this research serves as an exploration of online communication within the context of nationwide events such as the pandemic, given their perceived effectiveness at staving the effects of social isolation across age groups. In particular, the focus will be mediating aspects of mental health, controlling for personal characteristics, and considering online and offline presence, using the 2018 to 2020 period as a clear separator of remote activity participation. Firstly, the role of loneliness on health will be examined to verify if there is a consistent negative effect on self-perceived physical health, and if this effect remains the same across all levels of loneliness when we take into account the presence of online communication tools and their overall use:

**H1**: Loneliness has a significant negative relationship with perceived physical health.

**H1b**: Online interaction significantly reduces the negative relationship between perceived physical health and loneliness at all levels of the latter.

Furthermore, emotional health will also be taken into account, given the significant relationship between happiness and overall wellbeing (Pittman, 2018). It should also be noted how individuals who might seem less satisfied of their real-world life might be more likely to be more satisfied with their virtual connections:

**H2a**: Loneliness has a significant negative relationship with perceived emotional happiness.

**H2b**: Online interaction significantly reduces the negative relationship between perceived emotional happiness and loneliness, but only at high levels of loneliness.

Finally, we examine the effects of Online Communities and Online Social Support on the social aspect of interpersonal communication, and how social cohesion is affected by having higher levels of online interaction to the detriment of offline interactions:

**H3**: Loneliness has a significant negative relationship with perceived social cohesion.

**H3b**: Online interaction has a significant negative relationship with perceived social cohesion, but only at low levels of loneliness.

# **Literature Review**

## **Social Isolation vs. Loneliness**

The difficulty of quantifying loneliness within a country stems from the subjective interpretation that this condition may entail, considering how it bases its roots on the specific conditions of the individual, as well as its perception of what it means to feels alone. For instance, DiJulio, Hamel, Muñana, and Brodie (2018) found that people with debilitating conditions, low income, single, or divorced, were more likely to report feeling lonely, to rates almost equal to those with an objective low number of friends within their social group. This type of loneliness could be interpreted as a perceived lack of social support and a loss of cohesion and trust for both established institutions and the community at large, much in the vein of Putnam’s definition of a social capital (Putnam, 2000). Literature based on this initial definition distinguishes social loneliness with emotional loneliness, the former being what was just described, while the latter being a factor of intimacy and depth of relationships that is more difficult to quantify (Prohaska et al., 2020).

This study specifically addresses emotional loneliness, which varies depending on the individual’s cognitive Comparison Level (CL) of friendship needs (Thibaut & Kelley, 1959); in other words, the number and depth of intimate relationships required for the fulfillment of a satisfying level of connectedness. Russel, Cutrona, McRae and Gomez (2012) further elaborate on a non-liner relationship between the number of friends one possesses and his cognitively desirable CL, as social groups extended past this limit may result in decreases in satisfaction equal to a lack of intimate relationships. It should be noted that consideration of one aspect of loneliness does not preclude another: development conditions may lead people to have differential ideals of social network depth, and other conditions, such as cultural differences (DiJulio, Hamel, Muñana, & Brodie, 2018), residential location (Van Beek & Patulny, 2021), and dramatic life events (i.e., COVID-19; Luchetti et al., 2020) may temper these expectations due to exogenous limitations.

As such, there should be a clear distinction between loneliness, which is caused by a lack of meaningful connections, as an accumulation of what Putnam defines as bridging social capital as opposed to bonding social capital[[4]](#footnote-4), and social isolation, which is a loss of connections paired with a restriction in establishing new ones (Holt-Lunstad & Steptoe, 2022). Although there are overlapping features between both, measurement of each tends to undermine measurement of the other, with functions of loneliness/social isolation scales varying depending on the concentration of feeling versus network extension subscales (Cramer & Barry, 1999). Of these, the UCLA Loneliness Scale (Russel, 1996) is the most widely used, with the Social and Emotional Loneliness Scale for Adults (SELSA; DiTommaso & Spinner, 1993) and de Jong-Gierveld Loneliness Scale (Jong-Gierveld, 1987) standing in at a close second. It’s important to notice how most of these scales measure loneliness (Figure 1); this should not only be attributed to the inherent difficulty of measuring loneliness, but also to the contextual inability to truly be socially disconnected from others in an age of digital information (Marlowe, Bartley, & Collins, 2017).

## **Lonely Connections**

The continuous rise of connectivity rates across the U.S. might have been the reason why social isolation scales have progressively become outdated, as the 93% of Americans who claim to have used the internet in 2021 vastly outsource their 2000 counterparts (52%) in communication freedom and tools availability (Pew Research Center, 2021). This entails a higher level of social support distribution across all members of society, though preexisting inequalities can persist through proxy factors of socioeconomic and racial inequalities, such as internet broadband access, technological education, and choice of primary tech use (Le-Phuong, Lams, & De Cock, 2022). Regardless, gaps in age, race, and gender have been closing up when considering modern internet use[[5]](#footnote-5), and the pandemic has exacerbated this trend due to the physical restrictions of social isolation. In particular among young adults, internet participation has become more essential than ever (from 62% in 2020 to 72% in 2021; McClain, Vogels, Perrin, Sechopoulos & Rainie, 2021), due to its function as an information sharing platform, distant communication method, research, and emotional sharing tool (Wong, Ho, Olusanya, Antonini & Lyness, 2021).

Nevertheless, the presumption that offline and online communication and relationship building are fundamentally different remains valid. While platforms like social media allow us to remain, at least in part, connected with our family, friends, colleagues and acquaintances, their relational outputs allow for a relative perception of connectedness without necessarily reducing social isolation (Steafnone, Huang, & Lackaff, 2011). Even if we don’t take into account the negative aspects of online communication[[6]](#footnote-6), online interaction remains inferior to face-to-face interactions in its ability to provide strong and intimate relationship without the need of offline support (Ahn & Shin, 2013). In fact, both Bekalu (2021) and Kim (2019) only report the positive effect of social media engagement on social cohesion and efficacy within neighborhoods whose social network system was embedded with local infrastructure (e.g., Integrated Community Storytelling Networks); yet this still places online communications systems as an internet supported integration of offline relationships (Scott, Stuart, & Barber, 2021).

Now, the role that online communication has in reducing or advancing face-to-face interactions is still ambiguous, as some papers discuss the case wherein public use of internet access can enable greater chances for the enhancement of offline interactions (Lee & Lee, 2010; Yu, Mccammon, Ellison, & Langa, 2016), and redirect attention to the positive effect of connective areas of interaction within neighborhoods (Fong, Cruwys, Robinson, Haslam, Haslam, Mance & Fisher, 2021; Bergefurt, Kemperman, van den Berg, Borgers, van der Waerden, Oosterhuis & Hommel, 2019). Further, online tools provide opportunities for diversification of private clusters of communication within one’s close-tie network (Hampton, Livio, & Goulet, 2021), and an avenue for introduction of community norms and identity for otherwise disconnected individuals or groups (van Eldik, Kneer, Jansz, 2019). Others however, like Kearns and Whitley (2019), or Fawcett and Karastoyanova (2022), while they recognize the internet’s “reconnecting” potential, especially for vulnerable groups like seniors during pandemic times, continue to point at the fundamental differences between patterns of online and offline communication, which bring differential benefits within similar contexts of interaction.

## **The Unicity of Online Talk**

Quite simply, as a support tool for offline communication, online interaction and its consequently formed relationships represent a static copy of the former, with a distorted reproduction of the cognitive consistencies needed for an effective relationship. For example, Biester’s (2020; 2021) groups of research found that, even across different online communities, real-life aggregative events like COVID-19’s social isolation measures modified topic and word choice towards similar clusters of reference, such as redirecting mental health support search towards symptoms common to the pandemic: anxiety, fear of the new normal, depression etc.; a change that can be verified even at a linguistic level (Low, Rumker, Talkar, Torous, Cecchi, & Gosh, 2020). This phenomenon points at a connection between the personal self and the online self, and a similar synthesis of reciprocity groups that form across individual commonalities within the network (Cover, 2019)[[7]](#footnote-7). In other words, it allows for a simple transfer of social network benefits between online and offline relationships, meaning that increasing one’s social capital online is equal to doing so offline (Holmberg, 2014).

However, this implies a duality of identity that does not seem sustainable in the long run, and its benefits can only be enjoyed through continued commitment of both, more so of one’s online counterpart (Zhang & Sung, 2021). Neglecting the latter leads to the observed prevalence of weak ties across online interactions, and the preference of topic-based communities over reciprocity groups (Gil de Zúñiga & Valenzuela, 2011)[[8]](#footnote-8), which creates a problem in correctly quantifying the profitability of engaging in online communities versus physical ones. In fact, having already cited the limitations of face-to-face interaction, in particular regarding its requirement of geographical proximity, the unrestrained access of online communication exacerbates issues[[9]](#footnote-9) of causality and personal judgement of well-being in a community context (Atkinson, Bagnall, Corcoran, South, & Curtis, 2020). Contradictions are then formed among those who benefit from prioritizing either their online counterpart (Chopik, 2016) or their offline identity (Shakya & Christakis, 2017), and those that misinterpret their need for offline connectedness, often due to high loneliness, as a drive for online network expansion (Kim, 2017; Witz, Tucker, Briggs, & Schoemann, 2021; Pittman, 2018)

The reason cycles back to the unperceived inferiority of online over offline communication; that is, the prevalence of online bridging, weak, ties of relationship which are easier to form, maintain, and reconstruct. Considering the concurrent presence of outlier bonding, strong, ties deriving from either offline transposition or weakening of the benefits of offline identities (Filiposka, Gajduk, Dimitrova, & Kocarev, 2017), online engagement negatively impacts an individual’s happiness and increases marginalization due to age, race, relationship status, or income (Forthman, Colaizzi, Yeh, Kuplicki, & Paulus, 2021). In fact, while weak ties can benefit individuals by increasing perceived connectedness, as already discussed, the lack of a real output of social capital (i.e., trustworthy social nets, emotional support, physical aid etc.; Lee & Lee, 2010; Vacchiano & Bolano, 2021) creates a sense of disengagement that is not rationalized as a consequence of online presence, but as a deficiency of the latter (Kim, 2017; Pittman, 2018). In other words, the more lonely, unhealthy, or unwell a person feels while using social media, or other online communication apps, to reduce their discomfort, the less they will attribute this discomfort to this use.

## **Social Media, Health and Feeling Alone**

The self-fulfilling cycle of problematic internet use is a worrying determinant of the country’s health, as already negative aspects of both social isolation and perceived loneliness are worsened by the individuals’ engagement in dysfunctional communication patterns. The risks of continued loneliness and social isolation does not only affect the realm of mental health, but also behavioral and psychosomatic determinants of wellbeing such as Strokes, Suicidal Thoughts, Depression, Anxiety, Chronic Health Conditions, and Dysfunctional Health Behaviors (Park et at., 2020; Figure 2)[[10]](#footnote-10). In fact, in their 2018 Kaiser Foundation report, DiJulio et al. (2018) found that people in the U.S. considered declines in mental and physical health to be the worst consequences of prolonged loneliness (58% and 55%, compared to the 49% of declines in personal relationship quality), while meta-analyses by Holt-Lunstad and his research groups (2015, 2022) confirmed the causal mortality of social isolation, loneliness, and living alone (increases of 29%, 26%, and 32% respectively). Other literature goes deeper into the specific effects per each condition:

***Cardiovascular Diseases****.* Individuals at the higher spectrum of loneliness can experience increases of up to 14.4 mmHg of systolic blood pressure, leading to severe hypertension, and higher chances of atherosclerosis (Xia & Li, 2018). In addition, their incidence of coronary heart diseases and stroke was 1.29 times higher than people in the lower part of the spectrum (Paul, Bu, & Fancourt, 2021). Rates remain the same across age and gender, but older adults are reported to feel these effects more from real rather than perceived social isolation (National Academy of Sciences, Engineering, and Medicine; NASEM, 2020).

***Cognition and Self-Reported Health****.* The worst outcomes are found across seniors and people with underlying mental conditions, such as schizophrenia, obsessive compulsive disorders, bipolar disorder etc., finding an increased rate of impairment and longer times for remissions (Wang, Mann, Lloyd-Evans, Ma, & Johnson, 2018; NASEM, 2020). People over 65, in particular, tend to find most troublesome consequences, with 30% of the senior sample in Hämmig’s (2019) study of loneliness’s generational health effects reporting a general decline in self-rated health; a finding confirmed by increasing rates of Alzheimer’s dementia across abandoned elderly (Luanaigh & Lawlor, 2008)

***Depression and Anxiety****.* The association between loneliness, social isolation, and mental health comes both from a biomedical explanation of hormonal and organic dysfunction, such as cortical accumulation and HPA axis inflammation, and a maladaptive social cognition framework, which can be addressed with therapy or pharmaceuticals (Park et al., 2020). In fact, emotional, rather than social loneliness, is associated with higher incidence of major depressive disorders and generalized anxiety disorders (Hyland et al., 2019). The combined effect of previous mental conditions further reports an increase of suicidal ideation and suicide attempts when combined with both real and perceived isolation (30.44 and 4.37 Odds-Ratio respectively; Stickley & Koyanagi, 2016)

***Chronic Health Conditions and Health Behaviors***. The cognitive disassociation of social isolation and loneliness creates higher risk for worsening of pre-existing conditions and engagement in dysfunctional activities such as smoking, drinking, drug use, unhealthy diets, and physical inactivity, with prevalence rates increasing by 15% to 20% between higher and lower loneliness distributions (Hammig, 2019). The isolation forced by the pandemic did not aid those who were trying to improve their coping strategies, as opportunities for change were limited during quarantine and stay-at-home orders (Brewer et al., 2022); an even more worrying fact for elders, whose interruption therapeutic activities could result in greater losses in functional mobility and independency (NASEM, 2020).

A severe limitation common to all studies of health and loneliness associations is the focus and misinterpretation that occurs between determining what constitutes loneliness and what constitutes social isolation (Holt-Lunstad, Smith, Baker, Harris & Stephenson, 2015, Luanaigh & Lawlor, 2008), usually addressing one or the other without considering the connection between the two. The expansion of support groups online, and the change in ratios of bonding and bridging groups not only across platforms but also across time (Norris, 2002)[[11]](#footnote-11), renders determining “isolation” even more difficult, thus guiding research towards subjective determinants of loneliness. A noteworthy facilitator of this approach is the rise of social media, with specific attention given to the increase in use within the older age bracket, and inglobation of smaller site-based groups within larger platform-based communities (Mander, Buckle, & Moran, 2020). It’s clear then that “feeling alone” is not quite the same as “being alone” anymore, and happiness and health factors come to be mediated by quality, rather than expansiveness of social connections (Pittman, 2018).

## **Social Engagement as a Mediator between Health and Social Isolation**

Since personal evaluations of loneliness are untrustworthy and objective analysis of social isolation become misleading due to the connectedness of a social media centered society, it becomes urgent to find a measure of effective social cognition and identification that may bridge the differences between online and physical communication. To this point, a successful analysis of the connection between social isolation/loneliness and individual health and relational outcomes can come from the inclusion of social belonging and identity setting within communities of interest (van Eldik, Kneer, & Jansz, 2019); in other words, the degree to which an individual’s commitment and trust to a community, real or online, leads to his direct participation, and the consequences that the latter brings back to the individual. Of course, what drives civic engagement and member health is the combined perception that the community is functional, and the degree to which it effectually coexists (Bjornstrom, Ralston & Kuhl, 2013), meaning that high levels of shared social capital will only improve general well-being, and positive community participation, if it is composed of strong relationship ties, and vice versa (Collins, Neal, & Neal, 2014; Procentese, De Carlo, & Gatti, 2019).

The literature provides an ample library of civic engagement measures, which do not depend on subjective, and thus variable, opinions on social cohesion and social capital, such as volunteering, charitable giving, political donation, contact of political representatives, voting, citizenship, political expression etc. (Atknison, Bagnall, Corcoran, South & Curtis, 2020). In addition, the causal research surrounding civic engagement also details potential confounding effects from sources outside of preferred mode of communication and network quality, with the most prevalent being religion (Whitehead & Stroope, 2015), cultural and national context (Crocetti, Jahromi, & Buchanan, 2012), temporal engagement[[12]](#footnote-12) (Wray-Lake, DeHaan, Shubert, & Ryan (2020), political ideology (Ferrucci, Hopp, & Vargo, 2019), and group heterogeneity (Costa & Khan, 2003). Accordingly, the latter two unite the areas of civic engagement, online communication, and well-being, since the openness of online communities tends to render them heterogeneous, and thus, as discussed in concurrent research, prone to less community involvement (Johnson, Zhang, & Bichard, 2010).

As established, social effectiveness and well-being is directly correlated with the perceived intimacy and strength of a person’s close relationship net (Lee, Chung, & Park, 2018), and the internet and social media allow for some form of connection that engages in the reinforcement of offline relationships while diversifying it according to the person’s interests (Wellman, Boase, Chen, 2002; McCully, Lampe, Sarkar, Velasquez, & Sreevinasan, 2011). However, social cohesion serves as a mediator towards the effect of perceived community disorder and self-rated health only if it is perceived at an individual level (Bjornstrom, Ralston, & Kuhl, 2013), or, in other words, if we just count the individual feeling of connectedness to the community rather than his real level of connectedness; the former being more prevalent within homogenous group types (Subramanian, Kubzansky, Berkman, Fay & Kawachi, 2006). In an online context where heterogeneity is common and weak relationships prevail, the absence of meaningful offline support may hinder community participation, even if real cohesion remains high, and while online communication finds prevalent use in information sharing and peer communication, the activity itself does directly increase a person’s involvement in the community, rather the quality of the relationship does (Moy, Manosevitch, Stamm, & Dunsmore, 2005)

## **Is all Engagement Created Equal**

We can see then how contradictory the area of online communication study can be, and how the position of loneliness and social isolation within the effect of increasing or decreasing wellbeing, health, and civic engagement can change depending on the definition, existing networks, and belonging. A further driver of study being the assumed roadway of influence that each type of relationship has on another. In fact, Kaufman, Rodriguez, Walsh, Shafranske and Harrell (2022) found that the influence of intimate relationship on wellbeing may potentially mask the beneficial effect of weaker peer relationships, as they become only significant with higher detachments from partners and family (Figure 3). An explanation for this is the change in the interpretative importance of the relationship itself, as the satisfaction of personal needs of connection and effectiveness (Demir, Şimşek, & Procsal, 2013; Demir & Davidson, 2013)[[13]](#footnote-13) occurs at all levels of intimacy, yet changes relevance depending on context (Demir, 2009).

A final note is then provided by High and Colleagues (2022), whose meta-analytical work on online communication and wellbeing represents the fundamental basis of this paper. In fact, it is claimed that the main reason behind the contradictory reports on the positive versus negative effects of social media may come from differences in perspective between communication-based and psychology-based research; thus, a difference in focus between devices and users. Meier and Reinecke further elaborate that current research lacks on intercommunicative pattern analysis, with a heavier concentration on message influx count and a significant omission on message content aggregation (2021). For example, studying political ideology extremism within online forums by counting engagement instead of intent could miscategorize those that wish to engage for the sake of discussion and not to instill their support for the ideology itself.

As such, this paper embraces a socio-technical perspective to the effect of social media on well-being and a person’s relationship network quality (Ellison, Pyle, & Vitak, 2022). It values contextual need of the online engagement when considering the current intent of the agent/user, evaluating if this falls within the area of social presentation, social capital or social support. By doing so, we are able to capture the lost nuances of why a person engages in online versus offline communication, while also maintaining the overall count of how he/she does it, and what they gain or lose from doing so.

**Data and Methods**

## **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[[14]](#footnote-14). 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[[15]](#footnote-15), 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 Study (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 (Howell, 2022).

The 2016-2020 panel collaborated with the American National Elections Study 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 each wave either accounting for a sub-sampling of nonrespondents and the 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[[16]](#footnote-16).

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 were 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 (0 = Have not done this in the past 12 months, 1 = Have done this in the past 12 months) 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 (2018) 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 and Son (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).[[17]](#footnote-17)

# **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 too 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 categories, 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 significant in both years.

**Table of Preliminary Ordered Logit Regressions**

|  |  |  |  |
| --- | --- | --- | --- |
|  | 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 |

First Row has *t-statistics*, while second row contains *p-value*

# **Next Steps**

The data is still formatted in a wide format which makes the analysis of fixed effects hard to implement. Further, the analysis of the required variables has made even the subset dataset hard to follow and feel bloated. The primary goals of this next session of thesis workshops will involve the modification of the data into a more digestible form, in order to prepare for analysis and ease the computational expense of the models. At such point, an Hausman test will precede the operationalization of the Fixed Effects or Random Effects model, although it is more likely that the former will be utilized for my three levels of ordered logit analysis.

Following this, changes in the base category of loneliness will enable a verification of any changes occurring at different areas of its distribution. The expected result is that, while the health effect will remain the same, the effect on happiness will increase at lower levels, while the effect on social cohesion will increase at higher levels. The main point of the research will be determined once the variables of communication methods, social contact, and political participation are added, to verify if the effects change at all levels of the loneliness distribution or only among its extreme tails.

Finally, age effects will be verified by limiting the sample to young adults and seniors separately, to infer if any difference is found. It is likely that this step of the analysis will be abandoned if restriction results in a more limited sample size, which would affect the statistical power of any findings. Overall estimates will then be reported across tables and figures for the purpose of drafting and discussing its conclusions.

# References

Ahn, D., & Shin, D. H. (2013). Is the social use of media for seeking connectedness or for avoiding social isolation? Mechanisms underlying media use and subjective well-being. *Computers in Human Behavior*, *29*(6), 2453-2462.

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

Atkinson, S., Bagnall, A. M., Corcoran, R., South, J., & Curtis, S. (2020). Being well together: individual subjective and community wellbeing. *Journal of Happiness Studies*, *21*(5), 1903-1921.

Auxier, B., & Anderson, M. (2021). Social media use in 2021. *Pew Research Center*, *1*, 1-4.

Baetschmann, G., Ballantyne, A., Staub, K. E., & Winkelmann, R. (2020). feologit: A new command for fitting fixed effects ordered logit models. *The Stata Journal*, *20*(2), 253-275.

Baetschmann, G., Staub, K. E., & Winkelmann, R. (2015). Consistent estimation of the fixed effects ordered logit model. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *178*(3), 685-703.

Bekalu, M. A., McCloud, R. F., Minsky, S., & Viswanath, K. (2021). Association of social participation, perception of neighborhood social cohesion, and social media use with happiness: Evidence of trade‐off (JCOP‐20‐277). *Journal of Community Psychology*, *49*(2), 432-446.

Bergefurt, L., Kemperman, A., van den Berg, P., Borgers, A., van der Waerden, P., Oosterhuis, G., & Hommel, M. (2019). Loneliness and life satisfaction explained by public-space use and mobility patterns. *International journal of environmental research and public health*, *16*(21), 4282.

Bergstrand, K., & Mayer, B. (2020). “The Community Helped Me:” Community Cohesion and Environmental Concerns in Personal Assessments of Post-Disaster Recovery. *Society & natural resources*, *33*(3), 386-405.

Bianchi, E. C., & Vohs, K. D. (2016). Social class and social worlds: Income predicts the frequency and nature of social contact. *Social Psychological and Personality Science*, *7*(5), 479-486.

Biester, L., Matton, K., Rajendran, J., Provost, E. M., & Mihalcea, R. (2020). Quantifying the effects of COVID-19 on mental health support forums. *arXiv preprint arXiv:2009.04008*.

Biester, L., Matton, K., Rajendran, J., Provost, E. M., & Mihalcea, R. (2021). Understanding the impact of COVID-19 on online mental health forums. *ACM Transactions on Management Information Systems (TMIS)*, *12*(4), 1-28.

Bjornstrom, E. E., Ralston, M. L., & Kuhl, D. C. (2013). Social cohesion and self-rated health: the moderating effect of neighborhood physical disorder. *American journal of community psychology*, *52*(3), 302-312.

Brewer, G., Centifanti, L., Caicedo, J. C., Huxley, G., Peddie, C., Stratton, K., & Lyons, M. (2022). Experiences of mental distress during COVID-19: Thematic analysis of discussion forum posts for anxiety, depression, and obsessive-compulsive disorder. *Illness, Crisis & Loss*, *30*(4), 795-811.

Carl, N., & Billari, F. C. (2014). Generalized trust and intelligence in the United States. *PloS one*, *9*(3), e91786.

Cham, H., Reshetnyak, E., Rosenfeld, B., & Breitbart, W. (2017). Full information maximum likelihood estimation for latent variable interactions with incomplete indicators. *Multivariate behavioral research*, *52*(1), 12-30.

Chopik, W. J. (2016). The benefits of social technology use among older adults are mediated by reduced loneliness. *Cyberpsychology, Behavior, and Social Networking*, *19*(9), 551-556.

Collins, C. R., Neal, J. W., & Neal, Z. P. (2014). Transforming individual civic engagement into community collective efficacy: The role of bonding social capital. *American journal of community psychology*, *54*(3), 328-336.

Crocetti, E., Jahromi, P., & Buchanan, C. M. (2012). Commitment to community and political involvement: A cross-cultural study with Italian and American adolescents. *Human affairs*, *22*(3), 375-389.

Cudjoe, T. K., Roth, D. L., Szanton, S. L., Wolff, J. L., Boyd, C. M., & Thorpe Jr, R. J. (2020). The epidemiology of social isolation: National health and aging trends study. *The Journals of Gerontology: Series B*, *75*(1), 107-113.

Cullen, R., & Sommer, L. (2010, January). Participatory democracy and the value of online community networks: An exploration of online and offline communities engaged in civil society and political activity. In *2010 43rd Hawaii International Conference on System Sciences* (pp. 1-10). IEEE.

Davern, M., Bautista, R., Freese, J., Morgan, S. L., & Smith, T. W. (Release 1a, 2022, April). General Social Survey Panel Data (2016-2020). <https://doi.org/10.17605/OSF.IO/HACZV>

DeMaris, A. (2018). Marriage advantage in subjective well-being: Causal effect or unmeasured heterogeneity?. Marriage & family review, 54(4), 335-350.

Demir, M. (2010). Close relationships and happiness among emerging adults. *Journal of Happiness Studies*, *11*(3), 293-313.

Demir, M., & Davidson, I. (2013). Toward a better understanding of the relationship between friendship and happiness: Perceived responses to capitalization attempts, feelings of mattering, and satisfaction of basic psychological needs in same-sex best friendships as predictors of happiness. *Journal of happiness studies*, *14*(2), 525-550.

Demir, M., Şimşek, Ö. F., & Procsal, A. D. (2013). I am so happy ‘cause my best friend makes me feel unique: Friendship, personal sense of uniqueness and happiness. *Journal of Happiness Studies*, *14*(4), 1201-1224.

DiJulio, B., Hamel, L., Muñana, C., & Brodie, M. (2018). Loneliness and social isolation in the United States, the United Kingdom, and Japan: An international survey. *The Economist & Kaiser Family Foundation*. Retried from <https://www.kff.org/other/report/loneliness-and-social-isolation-in-the-united-states-the-united-kingdom-and-japan-an-international-survey/>

DiTommaso, E., and Spinner, B. (1993). The development and initial validation of the Social and Emotional Loneliness Scale for Adults (SELSA). *Personality and Individual Differences*, *14*, 127–134.

Dunbar, R. I. (2021). Religiosity and religious attendance as factors in wellbeing and social engagement. *Religion, Brain & Behavior*, *11*(1), 17-26.

Ellison, N. B., Pyle, C., & Vitak, J. (2022). Scholarship on well-being and social media: A sociotechnical perspective. *Current Opinion in Psychology*, 101340.

Enders, C. K., & Bandalos, D. L. (2001). The relative performance of full information maximum likelihood estimation for missing data in structural equation models. *Structural equation modeling*, *8*(3), 430-457.

Fawcett, B., & Karastoyanova, K. (2022). Older people, loneliness, social isolation and technological mitigations: utilising experiences of the Covid-19 pandemic as we move forward. *The British Journal of Social Work*.

Ferrucci, P., Hopp, T., & Vargo, C. J. (2020). Civic engagement, social capital, and ideological extremity: Exploring online political engagement and political expression on Facebook. *New Media & Society*, *22*(6), 1095-1115.

Filiposka, S., Gajduk, A., Dimitrova, T., & Kocarev, L. (2017). Bridging online and offline social networks: Multiplex analysis. *Physica A: Statistical Mechanics and its Applications*, *471*, 825-836.

Fong, P., Cruwys, T., Robinson, S. L., Haslam, S. A., Haslam, C., Mance, P. L., & Fisher, C. L. (2021). Evidence that loneliness can be reduced by a whole-of-community intervention to increase neighbourhood identification. *Social Science & Medicine*, *277*, 113909.

Forthman, K. L., Colaizzi, J. M., Yeh, H. W., Kuplicki, R., & Paulus, M. P. (2021). Latent variables quantifying neighborhood characteristics and their associations with poor mental health. *International journal of environmental research and public health*, *18*(3), 1202.

Gil de Zúñiga, H., & Valenzuela, S. (2011). The mediating path to a stronger citizenship: Online and offline networks, weak ties, and civic engagement. *Communication Research*, *38*(3), 397-421.

Gioia, F., Fioravanti, G., Casale, S., & Boursier, V. (2021). The effects of the fear of missing out on people's social networking sites use during the COVID-19 pandemic: the mediating role of online relational closeness and individuals' online communication attitude. *Frontiers in Psychiatry*, *12*, 620442.

Glanville, J. L., Andersson, M. A., & Paxton, P. (2013). Do social connections create trust? An examination using new longitudinal data. *Social Forces*, *92*(2), 545-562.

Groenewegen, P., & Moser, C. (2014). Online communities: Challenges and opportunities for social network research. *Contemporary Perspectives on Organizational Social Networks*.

Gui, M., & Büchi, M. (2021). From use to overuse: Digital inequality in the age of communication abundance. *Social Science Computer Review*, *39*(1), 3-19.

Hämmig, O. (2019). Health risks associated with social isolation in general and in young, middle and old age. *PLoS One, 14*(7), e0219663.

Hampton, K. N., Livio, O., & Goulet, L. S. (2021). The social life of wireless urban spaces: internet use, social networks, and the public realm. In *Public Space Reader* (pp. 384-391). Routledge.

Hastings, O. P. (2016). Not a lonely crowd? Social connectedness, religious service attendance, and the spiritual but not religious. Social Science Research, 57, 63-79.

Hastings, O. P. (2018). Less equal, less trusting? Longitudinal and cross-sectional effects of income inequality on trust in US States, 1973–2012. *Social Science Research*, *74*, 77-95.

High, A. C., Ruppel, E. K., McEwan, B., & Caughlin, J. P. (2022). Computer-Mediated Communication and Well-Being in the Age of Social Media: A Systematic Review. *Journal of Social and Personal Relationships*, 02654075221106449.

Holmberg, L. (2014). Seeking social connectedness online and offline: Does happiness require real contact? (Doctoral dissertation).

Holt-Lunstad, J., & Steptoe, A. (2022). Social isolation: An underappreciated determinant of physical health. *Current Opinion in Psychology*, *43*, 232-237.

Holt-Lunstad, J., Smith, T. B., Baker, M., Harris, T., & Stephenson, D. (2015). Loneliness and social isolation as risk factors for mortality: a meta-analytic review. *Perspectives on psychological science*, *10*(2), 227-237.

Hout, M. (2016). Money and morale: Growing inequality affects how Americans view themselves and others. *The ANNALS of the American Academy of Political and Social Science*, *663*(1), 204-228.

Howell, D. (July 14, 2022). The American National Election Studies (ANES) awarded $14 million to study 2024 elections. *ANES* [Press Release]. Accessed on November 17, 2022. <https://electionstudies.org/anes-2024-award/>

Hwang, T. J., Rabheru, K., Peisah, C., Reichman, W., & Ikeda, M. (2020). Loneliness and social isolation during the COVID-19 pandemic. *International psychogeriatrics*, *32*(10), 1217-1220.

Hyland, P., Shevlin, M., Cloitre, M., Karatzias, T., Vallières, F., McGinty, G., ... & Power, J. M. (2019). Quality not quantity: loneliness subtypes, psychological trauma, and mental health in the US adult population. *Social psychiatry and psychiatric epidemiology*, *54*(9), 1089-1099.

Johnson, T. J., Zhang, W., & Bichard, S. L. (2010). United we stand? Online social network sites and civic engagement. In *A networked self* (pp. 193-215). Routledge.

Jong-Gierveld, J. (1987). Developing and testing a model of loneliness. *Journal of Personality and Social Psychology*, *53*, 119–128.

Kamalpour, M., Watson, J., & Buys, L. (2020). How can online communities support resilience factors among older adults. *International Journal of Human–Computer Interaction*, *36*(14), 1342-1353.

Kaufman, V., Rodriguez, A., Walsh, L. C., Shafranske, E., & Harrell, S. P. (2022). Unique Ways in Which the Quality of Friendships Matter for Life Satisfaction. *Journal of Happiness Studies*, 1-18.

Kearns, A., & Whitley, E. (2019). Associations of internet access with social integration, wellbeing and physical activity among adults in deprived communities: evidence from a household survey. *BMC Public Health*, *19*(1), 1-15.

Kim, J. H. (2017). Smartphone-mediated communication vs. face-to-face interaction: Two routes to social support and problematic use of smartphone. *Computers in Human Behavior*, *67*, 282-291.

Kim, J. H. (2021). The neighborhood effect of cognitive function on self-rated health: A population-based observational study. *Archives of Gerontology and Geriatrics*, *93*, 104285.

Kim, Y. C., Shin, E., Cho, A., Jung, E., Shon, K., & Shim, H. (2019). SNS dependency and community engagement in urban neighborhoods: The moderating role of integrated connectedness to a community storytelling network. *Communication Research*, *46*(1), 7-32.

Kotwal, A. A., Holt‐Lunstad, J., Newmark, R. L., Cenzer, I., Smith, A. K., Covinsky, K. E., ... & Perissinotto, C. M. (2021). Social isolation and loneliness among San Francisco Bay Area older adults during the COVID‐19 shelter‐in‐place orders. *Journal of the American Geriatrics Society*, *69*(1), 20-29.

Kripfganz, S. (2016). Quasi–maximum likelihood estimation of linear dynamic short-T panel-data models. The Stata Journal, 16(4), 1013-1038.

Larsen, R. (2011). Missing data imputation versus full information maximum likelihood with second-level dependencies. *Structural Equation Modeling: A Multidisciplinary Journal*, *18*(4), 649-662.

Lee, J., & Lee, H. (2010). The computer-mediated communication network: Exploring the linkage between the online community and social capital. *new media & society*, *12*(5), 711-727.

Lee, S., Chung, J. E., & Park, N. (2018). Network environments and well-being: An examination of personal network structure, social capital, and perceived social support. *Health communication*, *33*(1), 22-31

Lee, Y. C., Malcein, L. A., & Kim, S. C. (2021). Information and communications technology (ICT) usage during COVID-19: Motivating factors and implications. *International journal of environmental research and public health*, *18*(7), 3571.

Le-Phuong, L., Lams, L., & De Cock, R. (2022). Social media use and migrants’ intersectional positioning: A case study of Vietnamese female migrants. *Media and Communication*, *10*(2), 192-203.

Lewis, V. A., MacGregor, C. A., & Putnam, R. D. (2013). Religion, networks, and neighborliness: The impact of religious social networks on civic engagement. *Social science research*, *42*(2), 331-346.

Li, F., Luo, S., Mu, W., Li, Y., Ye, L., Zheng, X., Xu, B., Ding, Y., Ling, P., Zhou, M., & Chen, X. (2021). Effects of sources of social support and resilience on the mental health of different age groups during the COVID-19 pandemic. *BMC psychiatry*, *21*(1), 16. <https://doi.org/10.1186/s12888-020-03012-1>

Lim, C., & Putnam, R. D. (2010). Religion, social networks, and life satisfaction. *American sociological review*, *75*(6), 914-933.

Lin, S., Liu, D., Niu, G., & Longobardi, C. (2020). Active social network sites use and loneliness: the mediating role of social support and self-esteem. *Current Psychology*, 1-8.

Low, D. M., Rumker, L., Talkar, T., Torous, J., Cecchi, G., & Ghosh, S. S. (2020). Natural language processing reveals vulnerable mental health support groups and heightened health anxiety on reddit during covid-19: Observational study. *Journal of medical Internet research*, *22*(10), e22635.

Luanaigh, C. Ó., & Lawlor, B. A. (2008). Loneliness and the health of older people. *International Journal of Geriatric Psychiatry: A journal of the psychiatry of late life and allied sciences*, *23*(12), 1213-1221.

Luchetti, M., Lee, J. H., Aschwanden, D., Sesker, A., Strickhouser, J. E., Terracciano, A., & Sutin, A. R. (2020). The trajectory of loneliness in response to COVID-19. *American Psychologist*, *75*(7), 897.

Mander J., Buckle C., & Moran S. (2020). Social: GlobalWebIndex’s flagship report on the latest trends in social media. *GlobalWebIndex*. Retrieved from <https://amai.org/covid19/descargas/SocialGlobalWebIndex.pdf>

Marlowe, J. M., Bartley, A., & Collins, F. (2017). Digital belongings: The intersections of social cohesion, connectivity and digital media. *Ethnicities, 17*(1), 85-102.

McClain, C., Vogels, E. A., Perrin, A., Sechopoulos, S., & Rainie, L. (2021). The Internet and the pandemic. *Pew Research Center*. Retrieved from <https://www.pewresearch.org/internet/2021/09/01/the-internet-and-the-pandemic/>

McCully, W., Lampe, C., Sarkar, C., Velasquez, A., & Sreevinasan, A. (2011, October). Online and offline interactions in online communities. In *Proceedings of the 7th international symposium on wikis and open collaboration* (pp. 39-48).

Meier, A., & Reinecke, L. (2021). Computer-mediated communication, social media, and mental health: A conceptual and empirical meta-review. *Communication Research*, *48*(8), 1182-1209.

Mewes, J., Fairbrother, M., Giordano, G. N., Wu, C., & Wilkes, R. (2021). Experiences matter: A longitudinal study of individual-level sources of declining social trust in the United States. *Social Science Research*, *95*, 102537.

Mohnen, S. M., Groenewegen, P. P., Völker, B., & Flap, H. (2011). Neighborhood social capital and individual health. *Social science & medicine*, *72*(5), 660-667.

Moy, P., Manosevitch, E., Stamm, K., & Dunsmore, K. (2005). Linking dimensions of Internet use and civic engagement. *Journalism & Mass Communication Quarterly*, *82*(3), 571-586.

National Academies of Sciences, Engineering, and Medicine. (2020). *Social isolation and loneliness in older adults: Opportunities for the health care system*. National Academies Press.

National Vital Statistics System. (February 7, 2022). National marriage and divorce rate trends for 2000 – 2020. *National Center for Health Statistics (CDC)*. Accessed on November 18, 2022. <https://www.cdc.gov/nchs/data/dvs/national-marriage-divorce-rates-00-20.pdf>

Park, C., Majeed, A., Gill, H., Tamura, J., Ho, R. C., Mansur, R. B., ... & McIntyre, R. S. (2020). The effect of loneliness on distinct health outcomes: a comprehensive review and meta-analysis. *Psychiatry Research*, *294*, 113514.

Park, H. M. (2011). Practical guides to panel data modeling: a step-by-step analysis using stata. *Public Management and Policy Analysis Program, Graduate School of International Relations, International University of Japan*, *12*, 1-52.

Park, H. M. (2015). Linear regression models for panel data using SAS, Stata, LIMDEP, and SPSS.

Paul, E., Bu, F., & Fancourt, D. (2021). Loneliness and risk for cardiovascular disease: mechanisms and future directions. *Current cardiology reports*, *23*(6), 1-7.

Paxton, P. (1999). Is social capital declining in the United States? A multiple indicator assessment. *American Journal of sociology*, *105*(1), 88-127.

Pew Research Center (2021). Internet/Broadband Fact Sheet. Internet. *Science & Tech.* Accessed on October 18th, 2022 <https://www.pewresearch.org/internet/fact-sheet/internet-broadband/>

Pittman, M. (2018). Happiness, loneliness, and social media: perceived intimacy mediates the emotional benefits of platform use. *The Journal of Social Media in Society*, *7*(2), 164-176.

Powell, A., Bryne, A., & Dailey, D. (2010). The essential Internet: Digital exclusion in low‐income American communities. *Policy & Internet*, *2*(2), 161-192.

Procentese, F., De Carlo, F., & Gatti, F. (2019). Civic engagement within the local community and sense of responsible togetherness. *TPM: Testing, Psychometrics, Methodology in Applied Psychology*, *26*(4).

Prohaska, T., Burholt, V., Burns, A., Golden, J., Hawkley, L., Lawlor, B., ... & Fried, L. (2020). Consensus statement: loneliness in older adults, the 21st century social determinant of health? *British Medical Journal open*, *10*(8), e034967.

Putnam, R. D. (2000). *Bowling alone: The collapse and revival of American community*. Simon and schuster.

Rauschenberg, C., Schick, A., Goetzl, C., Roehr, S., Riedel-Heller, S. G., Koppe, G., ... & Reininghaus, U. (2021). Social isolation, mental health, and use of digital interventions in youth during the COVID-19 pandemic: A nationally representative survey. *European Psychiatry*, *64*(1).

Reddit & GlobalWebIndex (2019). The era of We and the rise of online communities. *GlobalWebIndex*. Retrieved from <https://www.redditinc.com/assets/case-studies/TheEraOfWe.1.6.20.pdf>

Ren, Y., Kraut, R., & Kiesler, S. (2007). Applying common identity and bond theory to design of online communities. *Organization studies*, *28*(3), 377-408.

Riedl, M., & Geishecker, I. (2014). Keep it simple: estimation strategies for ordered response models with fixed effects. *Journal of Applied Statistics*, *41*(11), 2358-2374.

Russell, D. W. (1996). UCLA Loneliness Scale (Version 3): Reliability, validity, and factor structure. *Journal of Personality Assessment, 66*(1), 20–40. [https://doi.org/10.1207/s15327752jpa6601\_2](https://psycnet.apa.org/doi/10.1207/s15327752jpa6601_2)

Russell, D. W., Cutrona, C. E., McRae, C., & Gomez, M. (2012). Is loneliness the same as being alone? *The Journal of psychology*, *146*(1-2), 7-22.

Scott, R. A., Stuart, J., & Barber, B. L. (2021). Contemporary friendships and social vulnerability among youth: Understanding the role of online and offline contexts of interaction in friendship quality. *Journal of Social and Personal Relationships*, *38*(12), 3451-3471.

Sessions, L. F. (2010). How offline gatherings affect online communities: when virtual community members ‘meetup’. *Information, Communication & Society*, *13*(3), 375-395.

Smith, T. W., & Son, J. (2010). *An analysis of panel attrition and panel change on the 2006-2008 General Social Survey Panel*. NORC/University of Chicago.

Steafnone, M. A., Huang, Y. C., & Lackaff, D. (2011, January). Negotiating social belonging: Online, offline, and in-between. In *2011 44th Hawaii International Conference on System Sciences* (pp. 1-10). IEEE.

Stickley, A., & Koyanagi, A. (2016). Loneliness, common mental disorders and suicidal behavior: Findings from a general population survey. *Journal of affective disorders*, *197*, 81-87.

Subramanian, S. V., Kubzansky, L., Berkman, L., Fay, M., & Kawachi, I. (2006). Neighborhood effects on the self-rated health of elders: uncovering the relative importance of structural and service-related neighborhood environments. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, *61*(3), S153-S160.

Thibaut, J. W., & Kelley, H. H. (1959). The social psychology of groups. New York: Wiley.

Towner, E., Tomova, L., Ladensack, D., Chu, K., & Callaghan, B. (2022). Virtual social interaction and loneliness among emerging adults amid the COVID-19 pandemic. *Current Research in Ecological and Social Psychology*, *3*, 100058.

Turner, J. W., Grube, J. A., & Meyers, J. (2001). Developing an optimal match within online communities: An exploration of CMC support communities and traditional support. *Journal of Communication*, *51*(2), 231-251.

Vacchiano, M., & Bolano, D. (2021). Online and offline leisure, relatedness and psychological distress: A study of young people in Switzerland. *Leisure Studies*, *40*(3), 338-351.

Vaisey, S., & Miles, A. (2017). What you can—and can’t—do with three-wave panel data. *Sociological Methods & Research*, *46*(1), 44-67.

Valtorta, N. K., Kanaan, M., Gilbody, S., & Hanratty, B. (2016). Loneliness, social isolation and social relationships: what are we measuring? A novel framework for classifying and comparing tools. *British Medical Journal open*, *6*(4), e010799.

Van Beek, M., & Patulny, R. (2022). 'The threat is in all of us': Perceptions of loneliness and divided communities in urban and rural areas during COVID‐19. *Journal of Community Psychology*, *50*(3), 1531-1548.

van Eldik, A., Kneer, J., & Jansz, J. (2019). Urban & online: Social media use among adolescents and sense of belonging to a super-diverse city. *Media and Communication*, *7*(2), 242-253.

Villalonga-Olives, E., Adams, I., & Kawachi, I. (2016). The development of a bridging social capital questionnaire for use in population health research. *SSM-population Health*, *2*, 613-622.

Wang, J., Mann, F., Lloyd-Evans, B., Ma, R., & Johnson, S. (2018). Associations between loneliness and perceived social support and outcomes of mental health problems: a systematic review. *BMC psychiatry*, *18*(1), 1-16.

Weissbourd, R., Batanova, M., Lovison, V., & Torres, E. (2021). How the Pandemic Has Deepened an Epidemic of Loneliness and What We Can Do About It (pp. 1–13). *Harvard University*. Retrieved from <https://static1.squarespace.com/static/5b7c56e255b02c683659fe43/t/6021776bdd04957c4557c212/1612805995893/Loneliness+in+America+2021_02_08_FINAL.pdf>

Wellman, B., Boase, J., & Chen, W. (2002). The networked nature of community: Online and offline. *It & Society*, *1*(1), 151-165.

Whitehead, A. L., & Stroope, S. (2015). Small groups, contexts, and civic engagement: A multilevel analysis of United States Congregational Life Survey data. *Social Science Research*, *52*, 659-670.

Williams, R., Allison, P. D., & Moral-Benito, E. (2018). Linear dynamic panel-data estimation using maximum likelihood and structural equation modeling. *The Stata Journal*, *18*(2), 293-326.

Wirtz, D., Tucker, A., Briggs, C., & Schoemann, A. M. (2021). How and why social media affect subjective well-being: multi-site use and social comparison as predictors of change across time. *Journal of Happiness Studies*, *22*(4), 1673-1691.

Wong, A., Ho, S., Olusanya, O., Antonini, M. V., & Lyness, D. (2021). The use of social media and online communications in times of pandemic COVID-19. *Journal of the Intensive Care Society*, *22*(3), 255-260.

Wray-Lake, L., DeHaan, C. R., Shubert, J., & Ryan, R. M. (2019). Examining links from civic engagement to daily well-being from a self-determination theory perspective. *The Journal of Positive Psychology*, *14*(2), 166-177.

Xia, N., & Li, H. (2018). Loneliness, social isolation, and cardiovascular health. *Antioxidants & redox signaling*, *28*(9), 837-851.

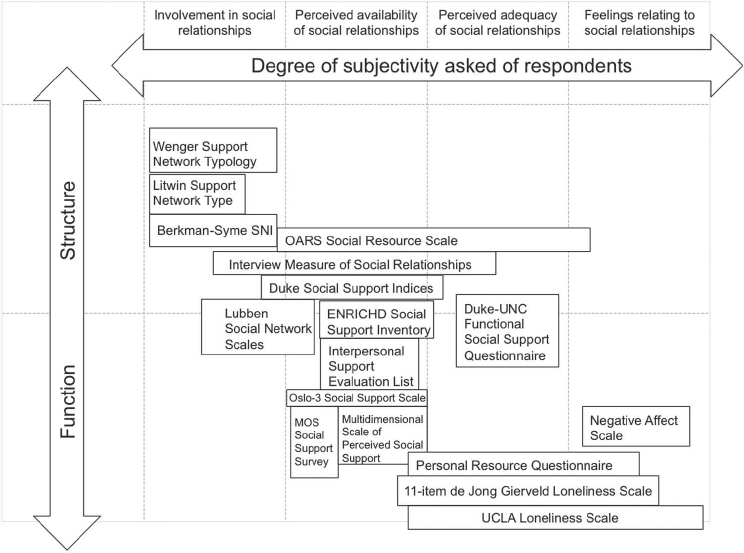
Yang, Y., & Land, K. C. (2008). Age–period–cohort analysis of repeated cross-section surveys: fixed or random effects? *Sociological methods & research*, *36*(3), 297-326.

Yu, R. P., Mccammon, R. J., Ellison, N. B., & Langa, K. M. (2016). The relationships that matter: Social network site use and social wellbeing among older adults in the United States of America. *Ageing & Society*, *36*(9), 1826-1852.

Zhang, S., & Xiang, W. (2019). Income gradient in health-related quality of life—The role of social networking time. *International journal for equity in health*, *18*(1), 1-10.

Zhang, X. A., & Sung, Y. H. (2021). Communities Going Virtual: Examining the Roles of Online and Offline Social Capital in Pandemic Perceived Community Resilience-Building. *Mass Communication and Society*, 1-27.

# **Tables and Figures**

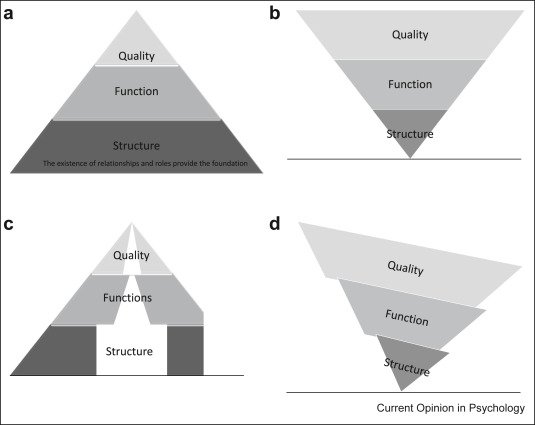


**Figure 1.** LonelinessScales ordered by study of relationship structure versus function, and subjectiveness of questionnaire (Valtorta, Kanaan, Gilbody, & Hanratty, 2016).

Diagram

Description automatically generated

**Figure 2.** Possible biochemical explanations of social isolation and loneliness effects of well-being and perceived health (Park et al., 2022).



**Figure 3.** Different types of social networks based on functionality and structure: **a)** bonding and bridging equilibrium, with little discomfort for the individual; **b)** prevalence of bonded relationships, but with sufficient support; **c)** large social network of shallow quality, typical of online interactions; **d)** prevalence of low-quality bonded relationships, which destabilize the individual (Holt-Lunstad & Steptoe, 2022).

1. The same Harvard study reported that 61% of the sample of young adults felt “severe loneliness” in the month of October 2020 [↑](#footnote-ref-1)
2. Results are cross referenced from the National Health and Aging Trends Study (NHATS) and an independent study by the Kaiser Foundation [↑](#footnote-ref-2)
3. 4,623 adults were interviewed by the collaborating agencies [↑](#footnote-ref-3)
4. “Bonding social capital refers to connections between members of a network who are similar to each other with respect to social class, race/ethnicity, or other attributes. By contrast, bridging social capital is defined as the connections between individuals who are dissimilar (or heterogeneous) with respect to socioeconomic and other characteristics” (Villalonga-Olives, E., Adams, I., & Kawachi) [↑](#footnote-ref-4)
5. While the view of digital equality here is optimistic, the literature also contends that focusing on praising growth rather than reinforcing it will lead to dangerous complacency, as new risks from the developing digital age remain unadressed (Gui & Bu¨ chi, 2021) [↑](#footnote-ref-5)
6. Cyberbullying, upward comparisons, fear of missing out, overuse, problematic internet use (Gioia, F., Fioravanti, G., Casale, S., & Boursier, 2021) [↑](#footnote-ref-6)
7. Cover (2019) specifically discusses the work that goes into creating and maintaining cognitive consistency across one’s friends and identity online, which directly copies our real-life work to avoid cognitive dissonance. [↑](#footnote-ref-7)
8. Ren, Kraut and Kiesler (2007) specifically reference Bond theory and the presence of common identity groups, which simplify their identity over the group’s existence, and bond groups, which function under intercommunicative relations across members. Topic-based groups are a simplification of the former, as norm guided entities with little empathy for existing members but attraction towards newcomer growth [↑](#footnote-ref-8)
9. Spatial and social inequalities, belonging to multiple communities at once, and temporal changes in well-being, as well as community structure types. [↑](#footnote-ref-9)
10. See Luchetti et al. (2020) and DiJulio, Hamel, Muñana, & Brodie (2018) for specific interrelationship characteristics [↑](#footnote-ref-10)
11. See Auxier and Anderson (2021) for specific site use [↑](#footnote-ref-11)
12. Time spent is the only factor that may vary between offline and online engagement. For details see Moy, Manosevitch, Stamm & Dunsmore (2005) [↑](#footnote-ref-12)
13. In both papers the sense of uniqueness is referenced as individuality within a shared community, which can be interpreted as usefulness without entailing intermember dependency. [↑](#footnote-ref-13)
14. Information obtained from the GSS website: <https://gss.norc.org/About-The-GSS> [↑](#footnote-ref-14)
15. 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-15)
16. 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-16)
17. 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-17)