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Internet use and physical and mental health in old age during the COVID-19 pandemic: Evidence from partners in SHARE☆

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ABSTRACT

Using data from the Survey of Health, Ageing and Retirement in Europe (SHARE), we investigate whether individuals aged 65 and older who were internet users prior to the COVID-19 pandemic experienced better physical and mental health, during the pandemic, than age peers who did not use the internet. We consider three health outcomes: self-reported health, overweight/obesity and depression. To account for household-shared determinants of health and reverse causality, we estimate household fixed effects regressions on samples of individuals grouped into households of cohabiting partners who exhibited identical pre-pandemic health outcomes. On average, our estimates point towards a non-significant effect of internet use on all health outcomes. The probability of depression varied by age: pre-pandemic internet users in the age-range 65-70 were more likely to experience depression, whereas those aged over 80 were less likely to be depressed, compared to internet nonusers in the same age-range. Moreover, we find that, among older pre-pandemic internet nonusers, those with stronger social ties had better access to remote medical consultations during the pandemic; this result suggests that social capital may play a protective role and may contribute to bridging the digital divide. We conclude that, although internet use holds significant potential benefits for older adults, its impact, particularly on mental health, is complex and multifaceted. Future interventions should be tailored to address these nuances, promoting beneficial uses of digital technology while mitigating its adverse effects.

1. Introduction

Population ageing is a global phenomenon and Europe is one of the regions with the highest share of old age population. Besides population ageing, another relevant structural change that requires the attention of social scientists is the growing importance of digital technologies for social contacts and intergenerational relationships, and as determinants of health and predictors of inequalities (Zagheni, 2021).

The very idea that the lack of access to digital technologies may lead to social exclusion, and, ultimately, to inequality, is at the core of the well-established media studies literature on the digital divide. This divide highlights the demographic and socioeconomic disparities between those who can fully leverage Information Communication Technologies (ICTs) and those who cannot (Hargittai et al., 2019; Hargittai and Dobransky, 2017; Hunsaker and Hargittai, 2018; Dewan and Riggins, 2005). In this field, three different levels of digital divide have been identified: the first level examines differences in access to technology, the second level focuses on variations in technology usage, and the third level addresses disparities in the digital skills necessary to effectively utilise ICTs.

The specific needs and barriers faced by older adults in ICT access, usage, and the benefits derived from ICTs have led to the concept of the "grey digital divide" — the gap between younger and older generations across the first, second, and third levels of the digital divide (Millward, 2003; Chee, 2024). The "grey digital divide" is a major concern for policymakers, given the implications for the social inclusion and wellbeing of an ageing population.

Several studies have identified a relationship between internet use and health in old age (Hunsaker and Hargittai, 2018; Benda et al., 2020; Hamer and Stamatakis, 2014; König et al., 2018), but the direction of such association is not clear. While some authors have recognised that internet access and the ability to effectively use the ICTs are social determinants of health (Benda et al., 2020; Zagheni,

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2021), others (e.g., König et al. 2018) have interpreted the association between self-reported health and internet use in old age as evidence that older adults with health issues (e.g., visual, hearing and tactile impairments) face challenges in using digital technologies. Adopting this latter interpretation, limitation in health seems to impede internet access, rather than internet access improving older people's health. Similarly, positive associations between internet use in old age and cognitive function (e.g., Hamer and Stamatakis 2014, Wang et al. 2024), which may suggest a protective role of ICTs from cognitive decay, have also been interpreted as a sign that reduced cognitive function and functional status in old age prevents the effective use of digital technologies (Hunsaker and Hargittai, 2018).

By the same token, digital exclusion has been found to be associated with functional dependency (Lu et al., 2022), namely, the degree to which older adults rely on assistance from others to perform daily activities. However, as also noted by the authors, reverse causation cannot be excluded.

An important element to consider in analysing the relationship between digital inequalities and inequalities in health is the role of social relationships. On one hand, strong social networks (especially intergenerational) may support older people with limited digital skills in accessing welfare services (including healthcare), when these are available primarily online, with positive externalities on older people's health. On the other hand, lack of access to digital technologies might be associated with loneliness and social exclusion and hence with decreased mental health (Szabo et al., 2019). Indeed, the use of social media, video calls, and messaging applications are fundamental for intergenerational connectedness, especially when families live apart. More broadly, in contemporary societies, where socialisation is often mediated by technology, lack of digital skills may reduce the possibilities to create, maintain, and strengthen social relationships, which are important for mental health and wellbeing, and, ultimately, for physical health too.

In summary, digital and health inequalities are interconnected with social capital – the resources that individuals can access thanks to their membership to a social network (Bourdieu, 1986) – as support from ones' social network (either in the form of peer-to-peer support or as intergenerational support) can aid older people to overcome barriers in access and effective use of technology.

In this context, the COVID-19 pandemic has played a crucial role in shaping the (ongoing) process of digitalisation of societies, thereby increasing the necessity for individuals to utilise digital technologies in their daily activities (Hantrais et al., 2021). In early 2020, social-distancing measures were introduced by governments worldwide, to minimise the spread of the SARS-CoV-2 virus, and individuals were encouraged to limit, or avoid altogether, face-to-face contacts. This implied relying as much as possible on digitally mediated communication for accessing public services, applying for public benefits and funds, interacting with public bodies, accessing medical care, actively participating in the labour market (e.g., remote working, job searching), socialising with family and friends, and so on.

Not surprisingly, in some contexts, it has been reported that segments of the population who lacked access to digital technologies, or did not have adequate digital skills, had difficulties in accessing public services such as medical and digital care (Benda et al., 2020; Eruchalu et al., 2021). Also, during the lockdowns, non-physical contacts (e.g., by phone, e-mail, or the internet) have, to some extent, reduced the risk of depressive feelings, insomnia and anxiety (Arpino et al., 2021; García-Prado et al., 2022), even though in person communication (when possible) seems to have benefited mental health more than online communication (Skałacka and Pajestka, 2021). Not surprisingly, digital inequalities have been found to have exacerbated health inequalities during the pandemic, among individuals with severe mental illnesses (Spanakis et al., 2021).

Ultimately, the pandemic has provided a moment of discontinuity in the requirement of using digital tools for communication, socialisation and accessing services. In this respect, the pandemic represents an important case study for the analysis of the opportunities provided and challenges imposed by the ongoing digitalisation of societies, for the old age population.

In this study, we leverage this moment of discontinuity and use data from the Survey of Health, Ageing and Retirement in Europe (SHARE) to analyse the relationship between digital inequalities and health inequalities in old age, during the pandemic. Additionally, we investigate whether social capital had a role in attenuating inequalities in health among less digitally savvy older people. In this research, we consider the various inequalities forms as interrelated one another, using a multidimensional perspective (Anand et al., 2020).

Specifically, this paper answers the following research questions: (*i*) Did older pre-pandemic internet users experience better physical and mental health outcomes during the COVID-19 pandemic? Our hypothesis is that while, overall, physical and mental health might have, on average, deteriorated during the pandemic, those more digitally savvy experienced better health outcomes, possibly as a result of better access to healthcare; (*ii*) Among older pre-pandemic internet nonusers, did those with stronger social ties have better access to remote medical consultations during the COVID-19 pandemic? Our hypothesis posits that individuals with stronger pre-pandemic social ties were more likely to access telemedicine during the pandemic, based on the assumption that their social networks provided support in accessing and using the internet. We anticipate that this effect was particularly relevant for pre-pandemic nonusers of the internet, as those who were already internet users were likely capable of accessing telemedicine independently, without relying on peer or intergenerational network support.

To investigate the first research question, we employ the household fixed effects estimator on outcome-specific samples of individuals, aged over 65, grouped into households of size two or more. The outcomes that we consider are self-reported health, overweight/obesity and depression, identified in accordance with the EURO-D scale (Prince et al., 1999). The households in our data are almost all composed of married or cohabiting partners of opposite sex who may share the household with other individuals who are not included in SHARE or do not fall within the 65+ age category.

We account for a comprehensive set of household-varying controls, and for all the household-shared determinants of physical and mental health through the household fixed effects estimator. Moreover, we account for pre-pandemic health statuses, and so for reverse causality, as we estimate the models on the outcome-specific subsamples of individuals who, within the household, exhibited identical pre-pandemic health outcomes. The fact that partners living in the same household shared the same environment and very similar experiences during the pandemic, especially during the lockdowns, reinforces the suitability of the household fixed effects estimator.

On average, our estimates point towards a non-significant effect of internet use on all health outcomes. The association between internet use and depression strongly depended on the age-range: individuals aged 65–70 who used the internet prior to the pandemic exhibited a higher probability of experiencing depression, whereas those over the age of 80 were less prone to depression, compared to their age-peers who were internet nonusers. Estimates based on models that do not account for pre-pandemic health outcomes suggest that internet users had higher probability of being overweight/obese and better self-reported health during the pandemic.

We estimate similar models to investigate the second research question and find that, as expected, the size of the social network increased the probability of accessing remote medical consultations only for those who were internet nonusers before the pandemic. This association was stronger in males who, before the pandemic, reported being neither sad nor depressed and in females who, before the pandemic, reported having either poor or excellent health.

2. Data

2.1. SHARE data

To address our research aims, we use data from SHARE, wave 8, SHARE Corona Survey 2 (SCS2) and wave 9 (Bergmann et al., 2022; Börsch-Supan and Jürges, 2005; Börsch-Supan et al., 2013). SHARE is a large-scale multidisciplinary and cross-national longitudinal dataset of more than 140,000 individuals, aged over 50, from 27 European countries and Israel. It collects individual-level data on a variety of topics, including health, socioeconomic status, and social networks. Wave SCS2 includes a specific questionnaire that covers the same topics as the regular SHARE questionnaire, albeit in a significantly shortened format tailored to the COVID-19 situation.

2.2. Sample selection

Our analyses are focused on individuals aged over 65. The SHARE data includes 35,358 individuals of this age-range interviewed between October 2019 and March 2020, in wave 8, before the onset of the COVID-19 pandemic. Of the same age-range, 35,809 individuals were interviewed between June and August 2021, in wave SCS2, at the midpoint of the pandemic, and 46,038 individuals were interviewed between October 2021 and September 2022, in wave 9, near the end of the pandemic.

Of the 35,358 individuals recorded in wave 8, 10,456 live independently, 21,099 share their household with one other person, and 3,803 live with two or more individuals; data is available for 17,518 individuals aged 65+ living in the same household of size greater than one, with almost all (17,442) being partners.

Of the same 35,358 individuals recorded in wave 8, 9,130 are part of the oldest-old demographic, specifically those aged over 80. Within this group, 4,134 individuals live independently, 4,292 share their household with one other person, and 704 live with two or more individuals.

In 2018, according to statistics on housing and living conditions provided by Eurostat,[1] 58% of all men aged 65 years and over living in the EU-27 shared their household with a partner; the corresponding share of women of the same age was 39%. Therefore, it seems that individuals living in households with more than one member are adequately represented in SHARE.

We investigate the association between pre-pandemic internet use, observed in wave 8, and self-reported health, overweight/obesity and depression during the pandemic, observed either in wave SCS2 or in wave 9, as well as the interrelation between pre-pandemic internet use and social network size, observed in wave 8, and access to remote medical consultations during the pandemic, observed in wave SCS2. We do so by estimating household fixed effects models on outcome-specific samples of individuals who are grouped into households of size greater than one.

As the different outcomes are observed in two waves and the set of controls that we include in the outcome-specific models slightly varies, the sample size differs by outcome. For the inclusion in the outcome-specific sample, the individual must comply with the following five conditions: (*i*) the individual must be interviewed in wave 8, when internet use and social network size are measured; (*ii*) internet use and, for the outcome access to remote medical consultations, social network size must be observed for the individual interviewed in wave 8;[2] (*iii*) the outcome must be observed for the individual, in either wave SCS2 or wave 9, depending on the outcome; (*iv*) for the physical and mental health outcomes recorded in either wave SCS2 or wave 9, it is essential that the same outcomes are also recorded for the individual in wave 8, as the primary analyses rely on models estimated on subsamples of individuals who, within the household, exhibit identical levels of pre-pandemic health outcomes; (*v*) the control variables that we include in each model, which are collected in either wave 8, SCS2 or 9, must be observed for the individual.

2.3. Measures of interest

After the exclusion of those individuals who do not comply with the five conditions outlined above, we have data on only two individuals per household in the outcome-specific samples, and almost all these individuals are married or cohabiting partners of opposite sex. In Table A.1 in Appendix, we show the household composition by outcome-specific sample, including the percentage of partners (nearly 100%), of individuals sharing the household with one person only (around 88%), and of those (around 12%) sharing the household with additional individuals who are not included in the outcome-specific samples.[3] We do the same for the oldest-old segment of the outcome-specific samples (aged over 80). Tables 1 and 2 show the distribution of the categorical variables and the descriptive statistics of the non-categorical variables in the outcome-specific samples, respectively.[4]

As the primary analyses regarding our health measures rely on models estimated on subsamples of individuals who, within the household, exhibit identical levels of pre-pandemic health outcomes, in Tables A.2 and A.3 in Appendix we show the distribution of the categorical variables and the descriptive statistics of the non-categorical variables in the restricted samples used for the main analyses.

Our outcomes of interest include self-reported health, overweight/obesity, depression and access to remote medical consultations. Self-reported health is measured in five ordered classes (i.e., poor, fair, good, very good, excellent) and recorded in wave 8 and wave SCS2.[5] Overweight/obesity is a binary variable equal to 1 if the individual is overweight or obese, based on the body mass index (BMI), and equal to 0 otherwise. The BMI is classified into underweight ($BMI < 18.5$), normal weight ($18.5 \leq BMI < 25$), overweight ($25 \leq BMI < 30$), and obesity ($BMI \geq 30$),[6] and recorded in wave 8 and wave 9.

Depression is a binary variable equal to 1 if the individual is depressed, according to the EURO-D scale, and equal to 0 otherwise. The EURO-D scale ranges from 0 (not depressed) to 12 (very depressed), assessing items such as depression, pessimism, wishing death, guilt, sleep, interest, irritability, appetite, fatigue, concentration, enjoyment and tearfulness (Prince et al., 1999). The EURO-D score is recorded in wave 8 and wave 9. In our models, we use a binary depression instead of the EURO-D score because for more than 20% of the individuals in our data the EURO-D score is equal to 0, implying that a linear model with the EURO-D score as the dependent variable may not be the best approach (Humphreys, 2013).[7] Although the original cut-off score for the diagnosis of depression was 3/4 (Prince et al., 1999),

[1] See the official Eurostat website "Statistics Explained" - https://ec.europa.eu/eurostat/statistics-explained/.

[2] It is important to remark that internet use and social network size are obtained from wave 8, but the number of remote medical consultations during the pandemic is obtained from wave SCS2.

[3] The exclusion of these additional individuals from the outcome-specific samples is primarily due to their absence from SHARE or their age, as they are not 65+. In few cases, the exclusion is attributed to these individuals not meeting the five conditions outlined in Section 2.2.

[4] Notice that the different full samples have a highly significant degree of overlap, as evidenced by the similar number of observations within each sample.

[5] Self-reported health data is also recorded in wave 9. In the sensitivity analyses, we use self-reported health obtained from wave 9 as the dependent variable.

[6] In the overweight/obesity sample, there are only 75 individuals classified as underweight in wave 8 and 113 individuals in wave 9.

[7] In the sensitivity analyses, the EURO-D score is used as the dependent variable.

Table 1
Distribution of categorical variables, by outcome-specific sample.

	Sample			
	Self-reported health	Overweight/obesity	Depression	Remote medical consultations
Self-reported health (wave SCS2):				
Poor	9.34%			9.00%
Fair	33.59%			33.49%
Good	40.45%			40.62%
Very good	13.05%			13.27%
Excellent	3.56%			3.63%
Self-reported health:				
Poor				7.72%
Fair				31.91%
Good				41.24%
Very good				14.76%
Excellent				4.37%
BMI - categories (wave 9):				
Underweight		1.08%		
Normal weight		34.36%		
Overweight		42.20%		
Obese		22.36%		
Depression (wave 9)			9.03%	
Self-reported sadness/depression (wave SCS2)				26.72%
Self-reported sadness/depression				33.98%
Access to remote medical consultations (wave SCS2)				39.98%
Internet use	51.49%	54.85%	54.99%	52.14%
Female	50.01%	50.00%	50.01%	50.01%
Education:				
Low	34.70%	32.05%	32.34%	34.04%
Medium	41.56%	42.30%	42.36%	41.88%
High	23.74%	25.65%	25.30%	24.08%
Employment status:				
Retired	87.75%	89.04%	88.73%	87.90%
Employed	3.06%	3.07%	3.13%	3.15%
Unemployed	0.09%	0.11%	0.09%	0.08%
Disabled	0.52%	0.49%	0.42%	0.49%
Home maker	7.98%	6.75%	7.07%	7.82%
Other	0.59%	0.55%	0.57%	0.56%
Observations	9,794	10,454	10,330	9,430

Unless otherwise specified, variables are observed in wave 8.

Table 2
Descriptive statistics of non-categorical variables, by outcome-specific sample.

	Observations	Mean	Standard deviation	Minimum	Maximum
Self-reported health sample:					
Age (wave SCS2)	9,794	75.01	5.80	66	101
Wellbeing	9,794	37.48	6.13	12	48
Difference in months (wave 8/SCS2)	9,794	18.01	1.40	15	22
Overweight/obesity sample:					
BMI (wave 9)	10,454	26.99	4.50	12.19	64.64
Age (wave 9)	10,454	75.40	5.69	66	102
Wellbeing	10,454	37.98	5.94	12	48
Difference in months (wave 8/9)	10,454	25.51	2.68	19	34
Depression sample:					
EURO-D score	10,330	2.32	2.15	0	12
Age (wave 9)	10,330	75.31	5.65	66	97
Wellbeing	10,330	37.99	5.94	12	48
Difference in months (wave 8/9)	10,330	25.47	2.67	19	34
Remote medical consultations sample:					
Number of remote medical consultations (wave SCS2)	9,430	1.72	4.77	0	300
Social network size	9,430	2.87	1.61	0	7
Age (wave SCS2)	9,430	74.97	5.79	66	101
Wellbeing	9,430	37.59	6.11	12	48
Difference in months (wave 8/SCS2)	9,430	18.02	1.40	15	22

Unless otherwise specified, variables are observed in wave 8.

Table 3
Household fixed effects estimates on self-reported health, by sample.

	$y = 1$ if good+ self-reported health	
	Full sample	Constant pre-pandemic health in HH
Internet use × female	0.060**	0.029
	(0.023)	(0.030)
Internet use × male	0.039	0.010
	(0.024)	(0.028)
Female	−0.014	−0.010
	(0.016)	(0.019)
Age	−0.011***	−0.006*
	(0.003)	(0.003)
Wellbeing	0.026***	0.016***
	(0.002)	(0.002)
Difference in months (wave 8/SCS2)	0.034	0.032
	(0.053)	(0.054)
Education:		
Medium	0.013	−0.006
	(0.022)	(0.025)
High	0.011	−0.005
	(0.026)	(0.027)
Employment status:		
Employed	0.036	0.029
	(0.047)	(0.055)
Unemployed	0.346	0.501*
	(0.172)	(0.178)
Disabled	−0.090	−0.003
	(0.092)	(0.113)
Home maker	−0.020	−0.017
	(0.021)	(0.030)
Other	−0.156	−0.032
	(0.109)	(0.105)
Country fixed effects	Not identified	Not identified
Year and month fixed effects	Yes	Yes
Test sex-specific internet use: p-value	0.295	0.453
Number of observations	9,794	6,466
Number of couples	4,897	3,233

"Constant pre-pandemic health in HH" denotes the sample of individuals who, within the household, exhibit the same category of binary pre-pandemic self-reported health (either poor/fair or good/very good/excellent). "Test sex-specific internet use" is the test on whether the sex-specific coefficients of internet use are different. The standard errors (in parentheses) are clustered at the country level. The standard errors and the p-values are computed with the cluster-robust CR2 estimator (Bell and McCaffrey, 2002) and the t-distribution with the Imbens and Kolesar (2016) degrees of freedom, respectively. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4
Household fixed effects estimates on overweight/obesity, by sample.

	$y = 1$ if overweight/obese	
	Full sample	Constant pre-pandemic overweight/obesity in HH
Internet use × female	−0.012	−0.023
	(0.022)	(0.017)
Internet use × male	0.074***	−0.005
	(0.018)	(0.016)
Female	−0.026	0.003
	(0.026)	(0.012)
Age	−0.004	−0.003
	(0.003)	(0.002)
Wellbeing	−0.002	0.000
	(0.002)	(0.001)
Difference in months (wave 8/9)	0.042	0.000
	(0.051)	(0.038)
Education:		
Medium	−0.027	−0.002
	(0.019)	(0.012)
High	−0.044*	−0.024
	(0.022)	(0.019)
Employment status:		
Employed	0.017	0.031
	(0.038)	(0.039)
Unemployed	−0.176	0.159
	(0.214)	(0.190)
Disabled	−0.152	0.059
	(0.137)	(0.150)
Home maker	−0.032	0.002
	(0.031)	(0.016)
Other	−0.238**	−0.217*
	(0.091)	(0.098)
Country fixed effects	Not identified	Not identified
Year and month fixed effects	Yes	Yes
Test sex-specific internet use: p-value	0.004	0.372
Number of observations	10,454	6,394
Number of couples	5,227	3,197

"Constant pre-pandemic overweight/obesity in HH" denotes the sample of individuals who, within the household, exhibit the same category of binary pre-pandemic BMI (either overweight/obese or not overweight/obese). "Test sex-specific internet use" is the test on whether the sex-specific coefficients of internet use are different. The standard errors (in parentheses) are clustered at the country level. The standard errors and the p-values are computed with the cluster-robust CR2 estimator (Bell and McCaffrey, 2002) and the t-distribution with the Imbens and Kolesar (2016) degrees of freedom, respectively. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

more recent studies (Guerra et al., 2015; Jirapramukpitak et al., 2009; Prajwal et al., 2021) propose 5/6. We follow the latter approach for determining individuals who are depressed.[8]

Access to remote medical consultations is a binary variable equal to 1 if the individual utilises at least one remote medical consultation, from the onset of the pandemic up to the time of the interview in wave SCS2, and equal to 0 otherwise.[9]

Our regressors of interest include internet use and social network size. Internet use is a binary variable equal to 1 if the individual reports using the internet at least once in the 7 days preceding the interview, in wave 8. The size of an individual's social network is defined by the number of people within that network before the pandemic, which ranges from 0 to 7.

The main household-varying variables we account for in our models include age (at the time of the interview during the pandemic), and sex, education, employment status and wellbeing (all observed in wave 8), as well as the difference in months between wave 8 and either wave SCS2 or wave 9. The binary sex categorisation that we use (female/male) is the one assigned at birth and based solely on the visible external anatomy of the newborn. Education is observed in three classes, according to the International Standard Classification of Education 2011 (UNESCO, 2012): low (ISCED 0–1 and ISCED 2, namely, no or primary education, and lower secondary education, respectively), medium (ISCED 3–4, higher secondary education), and high (ISCED 5–6, tertiary education). Employment status is observed in six classes: retired, employed (including self-employed), unemployed, disabled, homemaker and other. As one can easily expect, the majority of the individuals aged over 65, in our sample, are retired.

[8] In the sensitivity analyses, we use the original cut-off score 3/4 for the diagnosis of depression.

[9] It is unclear whether remote medical consultations occurred primarily through online platforms or telephone calls; it is likely that both methods were utilised. Additionally, we do not have information about the specific types of appointments that were conducted via telehealth.

Table 5
Household fixed effects estimates on depression, by sample.

	$y = 1$ if 6+ EURO-D score	
	Full sample	Constant pre-pandemic depression in HH
Internet use × female	−0.012	−0.001
	(0.010)	(0.008)
Internet use × male	−0.014	−0.012
	(0.015)	(0.013)
Female	0.041***	0.025*
	(0.014)	(0.013)
Age	0.004	0.004*
	(0.002)	(0.002)
Wellbeing	−0.014***	−0.008***
	(0.001)	(0.002)
Difference in months (wave 8/9)	0.004	0.023
	(0.028)	(0.026)
Education:		
Medium	−0.004	−0.020
	(0.015)	(0.013)
High	−0.008	−0.017
	(0.013)	(0.013)
Employment status:		
Employed	−0.013	−0.009
	(0.028)	(0.023)
Unemployed	0.153	0.158
	(0.105)	(0.140)
Disabled	0.011	−0.023
	(0.079)	(0.090)
Home maker	0.030*	0.007
	(0.014)	(0.010)
Other	0.077	0.066
	(0.055)	(0.063)
Country fixed effects	Not identified	Not identified
Year month fixed effects	Yes	Yes
Test sex-specific internet use:		
p-value	0.905	0.452
Number of observations	10,330	9,226
Number of couples	5,165	4,613

"Constant pre-pandemic depression in HH" denotes the sample of individuals who, before the pandemic, are all either depressed or not depressed in the household, based on the 5/6 EURO-D threshold. "Test sex-specific internet use" is the test on whether the sex-specific coefficients of internet use are different. The standard errors (in parentheses) are clustered at the country level. The standard errors and the p-values are computed with the cluster-robust CR2 estimator (Bell and McCaffrey, 2002) and the t-distribution with the Imbens and Kolesar (2016) degrees of freedom, respectively. $^{*} p < 0.1$, $^{**} p < 0.05$, $^{***} p < 0.01$.

Wellbeing is based on the CASP-12 scale which assesses 12 items of quality of life, grouped into four dimensions: control, autonomy, self-realisation and pleasure. The items are rated on a four-point Likert scale (i.e., 1 = never, 2 = rarely, 3 = occasionally, 4 = often) which determines the final wellbeing score, ranging from 12 (worst quality of life) to 48 (best quality of life). The difference in months between wave 8 and either wave SCS2 or wave 9 is the number of months between the pre-pandemic interview (wave 8) and the interview during the pandemic (either in wave SCS2 or in wave 9, depending on the outcome). The difference in this difference is 0 within households in about 96% of cases, indicating that couples were typically interviewed simultaneously. In the remaining cases, the observed values range from 1 to 7.

In certain regressions, particularly when the outcome under investigation is access to remote medical consultations, we also account for additional variables. These include self-reported health, as previously defined, and self-reported sadness/depression, both before and during the pandemic. Self-reported sadness/depression is a binary variable equal to 1 if the individual reports being either sad, depressed or both, and equal to 0 otherwise.[10]

2.4. Wave 9, SHARE corona survey 2 and the COVID-19 pandemic

In Fig. 1 we plot the confirmed number of daily deaths due to the SARS-CoV-2 virus, from the onset to the formal end of the COVID-19 pandemic (March 11, 2020–May 5, 2023). As mentioned above, the individuals surveyed in wave SCS2 and wave 9 were interviewed at the midpoint and near the end of the pandemic, respectively. Depression and BMI data were collected in wave 9, with over 70% of individuals in the depression and overweight/obesity samples interviewed between November 2021 and March 2022, a period marked by a remarkably high number of daily deaths. In contrast, self-reported health data was collected in wave SCS2, in the summer of 2021, a time characterised by a significantly lower number of daily deaths.

In terms of travel restrictions, the wave-SCS2 period experienced a greater number of limitations compared to the wave-9 period. Between October 2021 and March 2022, various travel restrictions remained in effect across all SHARE countries, whereas by the end of September 2022, virtually no restrictions were in place in these countries. Table A.4 in Appendix provides a summary of these restrictions categorised by wave and key dates.

It is important to highlight that the interviews for waves SCS2 and 9 were carried out after the implementation of the COVID-19 vaccination protocol. From June 2021 to the end of August 2021, the proportion of the European population fully vaccinated against the SARS-CoV-2 virus increased from 17.6% to 48.0%, ultimately reaching a peak of 65.1% by the end of March 2022.[11] In many European countries, the vaccination efforts, particularly concerning the primer dose, prioritised the elderly population, among other groups (Van Kessel et al., 2023).

All considered, the overall conclusions based on the estimates of the models regarding our health measures may not fully represent the COVID-19 situation, considering the timing of the data collection.

3. Methods

3.1. Pre-pandemic internet use and health during the COVID-19 pandemic

The health outcomes y_i for individual i that we consider are a binary variable equal to 1 if self-reported health is good or above, and equal to 0 otherwise, a binary variable equal to 1 if the individual is overweight or obese, and equal to 0 otherwise, and binary depression, determined by the 5/6 threshold of the EURO-D score. All the health outcomes are measured during the COVID-19 pandemic. Define

$$y_i = \beta_1 f_i \cdot iu_i + \beta_2(1 - f_i) \cdot iu_i + \mathbf{x}_i\boldsymbol{\gamma} + \theta_{(i)j} + \epsilon_i, \tag{1}$$

where the index j denotes the household, iu_i is the binary variable for internet use, measured in wave 8, f_i is the binary variable for female, $(1 - f_i)$ is the binary variable for male, the vector $\mathbf{x}_i$ includes f_i, age (at the time of y_i being observed), and education, wellbeing and employment status (all observed in wave 8), as well as country of residence (via fixed effects, $p_{(i)c}$, for country c). Additionally, $\mathbf{x}_i$ includes the fixed effects $d_{(i)my}$, for the year $t = 2021, 2022$ and the month $m = 1, \ldots, 12$ of the interview during the pandemic. Finally, $\mathbf{x}_i$ includes the difference in months between the interview in wave 8 and the interview in either wave SCS2 or 9, depending on the specific outcome under investigation. The residual term is the sum of a component $\theta_{(i)j}$ shared among individuals in the same household j and an idiosyncratic component ϵ_i. The vector $\mathbf{x}_i$ does not include pre-pandemic health statuses because, by definition of model (1), they are endogenous and correlated with iu_i, since y_i depends on both ϵ_i and iu_i.

[10] We account for self-reported sadness/depression instead of depression based on the EURO-D score because the latter is not observed in wave SCS2, when data on remote medical consultations is collected.

[11] Source: ourworldindata.org.

Table 6
Household fixed effects average marginal effects of internet use on depression, by sex, age and sample.

	$y = 1$ if 6+ EURO-D score			
	Full sample		Constant pre-pandemic depression in HH	
	Female	Male	Female	Male
Age 65	0.035	0.054**	0.064***	0.045*
	(0.030)	(0.024)	(0.023)	(0.024)
70	0.011	0.024	0.029**	0.021
	(0.017)	(0.017)	(0.013)	(0.017)
75	−0.013	−0.005	−0.006	−0.004
	(0.012)	(0.014)	(0.009)	(0.013)
80	−0.038*	−0.035*	−0.041**	−0.028*
	(0.021)	(0.018)	(0.016)	(0.016)
85	−0.062*	−0.064**	−0.076***	−0.052**
	(0.034)	(0.026)	(0.027)	(0.022)
90	−0.086*	−0.094***	−0.112***	−0.077**
	(0.048)	(0.035)	(0.038)	(0.030)
Test internet use × female × age:				
p-value	0.118		0.006	
Test internet use × male × age:				
p-value		0.009		0.018
Number of observations	10,330		9,226	
Number of couples	5,165		4,613	

"Constant pre-pandemic depression in HH" denotes the sample of individuals who, before the pandemic, are all either depressed or not depressed in the household, based on the 5/6 EURO-D threshold. "Test internet use × female × age" and "Test internet use × male × age" are the tests on whether the interaction terms between internet use, sex (female and male, respectively) and age are significant. The standard errors (in parentheses) are clustered at the country level. The standard errors and the p-values are computed with the cluster-robust CR2 estimator (Bell and McCaffrey, 2002) and the t-distribution with the Imbens and Kolesar (2016) degrees of freedom, respectively. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

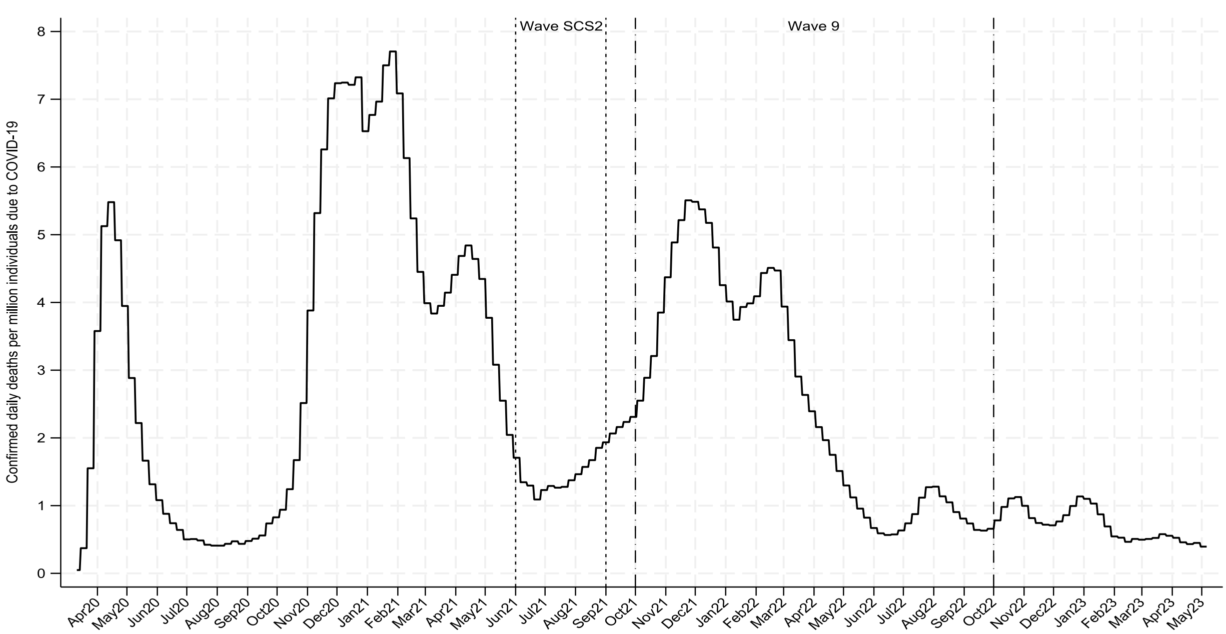

Fig. 1. Confirmed number of daily deaths per million individuals in Europe due to COVID-19.
Source: ourworldindata.org.

Table 7
Household fixed effects estimates on access to remote medical consultations, by sample.

	$y = 1$ if 1+ remote medical consultations		
	Full sample	Internet nonusers	Internet users
Social network size × female	0.015***	0.023**	0.008
	(0.005)	(0.010)	(0.008)
Social network size × male	0.017***	0.037***	0.006
	(0.005)	(0.009)	(0.007)
Female	0.013	0.056	−0.017
	(0.019)	(0.032)	(0.034)
Age	−0.000	0.001	−0.002
	(0.002)	(0.003)	(0.003)
Wellbeing	0.001	−0.000	0.003
	(0.002)	(0.003)	(0.003)
Difference in months (wave 8/SCS2)	−0.019	−0.033	−0.037
	(0.028)	(0.042)	(0.047)
Education:			
Medium	0.015	0.020	0.011
	(0.013)	(0.022)	(0.026)
High	0.022	0.008	0.029
	(0.017)	(0.052)	(0.034)
Employment status:			
Employed	−0.071**	−0.085	−0.103***
	(0.025)	(0.082)	(0.029)
Unemployed	0.162	0.018	0.096
	(0.143)	(0.044)	(0.095)
Disabled	−0.123*	−0.084	−0.083
	(0.057)	(0.051)	(0.168)
Home maker	0.005	−0.002	0.013
	(0.029)	(0.034)	(0.057)
Other	0.038	0.118	−0.042
	(0.053)	(0.066)	(0.156)
Self-reported health (wave 8):			
Fair	−0.043*	−0.047	−0.011
	(0.023)	(0.032)	(0.061)
Good	−0.067**	−0.090**	−0.002
	(0.028)	(0.035)	(0.069)
Very good	−0.068*	−0.049	−0.032
	(0.033)	(0.059)	(0.069)
Excellent	−0.117**	−0.248**	−0.033
	(0.044)	(0.084)	(0.089)
Self-reported health (wave SCS2):			
Fair	−0.011	0.016	−0.049
	(0.021)	(0.034)	(0.046)
Good	−0.062**	−0.054	−0.115**
	(0.022)	(0.045)	(0.050)
Very good	−0.112***	−0.087*	−0.167***
	(0.030)	(0.049)	(0.052)
Excellent	−0.204***	−0.110	−0.274***
	(0.033)	(0.077)	(0.052)
Self-reported sadness/depression (wave 8)	0.032**	0.015	0.062**
	(0.011)	(0.017)	(0.021)
Self-reported sadness/depression (wave SCS2)	0.038**	0.053**	0.034
	(0.017)	(0.021)	(0.026)
Country fixed effects	Not identified	Not identified	Not identified
Year and month fixed effects	Yes	Yes	Yes
Test sex-specific social network size: *p*-value	0.616	0.122	0.755
Number of observations	9,430	3,274	3,678
Number of couples	4,715	1,637	1,839

"Internet nonusers" denotes the sample of individuals who, before the pandemic (in wave 8), report not using the internet in the 7 days preceding the interview. "Internet users" denotes the sample of individuals who, before the pandemic (in wave 8), report using the internet at least once in the 7 days preceding the interview. "Test sex-specific social network size" is the test on whether the sex-specific coefficients of social network size are different. The standard errors (in parentheses) are clustered at the country level. The standard errors and the p-values are computed with the cluster-robust CR2 estimator (Bell and McCaffrey, 2002) and the t-distribution with the Imbens and Kolesar (2016) degrees of freedom, respectively.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

To mitigate the bias in the estimates of the sex-specific coefficients of internet use β_1 and β_2,[12] we estimate model (1) with the household fixed effects estimator[13] on the outcome-specific subsample of individuals who, within the household, exhibit the same binary pre-pandemic self-reported health outcome (either poor/fair or good/very good/excellent), binary BMI outcome (either overweight/obese or not overweight/obese), or binary depression outcome (either depressed or not depressed, based on the 5/6 EURO-D threshold), depending on the health outcome being investigated.[14] By doing so, the omitted pre-pandemic health outcome is absorbed by $\theta_{(i)j}$ and accounted for, together with all the household-shared determinants of y_i, by the household fixed effects estimator.

To gain insights on the bias of $\hat{\beta}_1$ and $\hat{\beta}_2$ if this strategy is not employed, we estimate model (1) with the household fixed effects estimator on the full outcome-specific samples.

Next, we extend model (1) by allowing interactions of internet use and age, defining

$$y_i = \beta_1 f_i \cdot iu_i + \beta_2(1-f_i)\cdot iu_i + \beta_3 f_i \cdot iu_i \cdot age_i + \beta_4(1-f_i)\cdot iu_i \cdot age_i + \beta_5 f_i \cdot age_i + \mathbf{x}_i\boldsymbol{\gamma} + \theta_{(i)j} + \epsilon_i. \tag{2}$$

Based on the estimates of model (2), and conditional on $\hat{\beta}_3$ and $\hat{\beta}_4$ being significantly different from 0, we estimate the average marginal effects (AMEs) of internet use,[15] by age and sex. The female-specific and male-specific estimated AMEs are $\hat{\beta}_1 + \hat{\beta}_3 age_i$ and $\hat{\beta}_2 + \hat{\beta}_4 age_i$, respectively.

3.2. Pre-pandemic internet use, social ties, and telemedicine during the COVID-19 pandemic

Define the vector $\mathbf{z}_i$ which includes self-reported health and sadness/depression, both observed in both wave 8 and wave SCS2, and the variable sn_i, which is the social network size, measured in wave 8. Consider the number of remote medical consultations during the COVID-19 pandemic, rmc_i. This variable is countable with many zeros, therefore estimating a linear model with log-transformed dependent variable, $\ln(rmc_i)$, is not a good approach (Cameron and Trivedi, 2013). Hence, we define $y_i = 0$ if $rmc_i = 0$ and $y_i = 1$ if $rmc_i > 0$, and estimate

$$y_i = \beta_1 f_i \cdot sn_i + \beta_2(1-f_i)\cdot sn_i + \mathbf{x}_i\boldsymbol{\gamma} + \mathbf{z}_i\boldsymbol{\pi} + \theta_{(i)j} + \epsilon_i \tag{3}$$

with the household fixed effects estimator on the full remote medical consultations sample. Additionally, we estimate the same model on the subsample of internet nonusers and on the subsample of internet users, to investigate if the association between pre-pandemic social network size and access to remote medical consultations during the pandemic is stronger for those with lower levels of internet use, and to account for spillover effects within the household.[16]

[12] Notice that model (1) is equivalent to the conventional specification $y_i = \alpha_1 iu_i + \alpha_2 f_i \cdot iu_i + \mathbf{x}_i\boldsymbol{\gamma} + \theta_{(i)j} + \epsilon_i$, where $\beta_2 = \alpha_1$ and $\beta_1 = \alpha_1 + \alpha_2$. This can be seen by rewriting model (1) as $y_i = \beta_2 iu_i + (\beta_1 - \beta_2) f_i \cdot iu_i + \mathbf{x}_i\boldsymbol{\gamma} + \theta_{(i)j} + \epsilon_i$. The advantage of model (1) relative to the conventional specification is that the sex-specific estimated coefficients of internet use, $\hat{\beta}_1$ and $\hat{\beta}_2$, are directly presented in the regression table.

[13] As nearly 100% of the individuals in our samples are partners, the estimator can be interpreted as a partner fixed effects estimator, provided that the partners reside in the same household.

[14] Notice that country fixed effects are not identified but still controlled for, through the household fixed effects estimator.

[15] We do not claim causality; rather, we adhere to the conventional, albeit potentially misleading, denomination.

[16] The term "spillover effects" refers to the phenomenon where cohabiting partners of older adults who do not use the internet may themselves use it and assist them in accessing remote medical consultations.

4. Results

In this section, we discuss the results based on the estimates of model (1), model (2) and model (3), along with additional results and sensitivity analyses that may be based on different specifications, models or estimators.[17] As the data is clustered in few countries, to account for the intracluster correlation of the error term, the household fixed effects regressions employ the cluster-robust CR2 estimator of the standard errors (Bell and McCaffrey, 2002), using the t-distribution with the Imbens and Kolesar (2016) degrees of freedom for inference. Additionally, we investigate if other cluster-robust estimators, such as CR3 (Bell and McCaffrey, 2002) and CR3-λ (Niccodemi and Wansbeek, 2022; Niccodemi et al., 2020), lead to different standard errors, detecting no significant variation.

4.1. Pre-pandemic internet use and health during the COVID-19 pandemic

4.1.1. Main results

In Table 3, we show the household fixed effects estimates of model (1), with binary self-reported health as the dependent variable. Based on the estimates on the subsample of individuals who, within the household, exhibit the same category of binary pre-pandemic self-reported health, neither female nor male internet users are significantly more likely to self-report good, very good or excellent health, during the COVID-19 pandemic. By estimating model (2) on the same subsample we find no significant interaction between age and internet use. Estimates on the full sample are likely biased, as they suggest a protective effect of internet use on health in females, but do not take into account pre-pandemic health.

Next, in Table 4, we show the household fixed effects estimates of model (1), with binary overweight/obesity as the dependent variable. Based on the estimates on the subsample of individuals who, within the household, are all either overweight/obese or not prior to the pandemic, neither female nor male internet users are more likely to be overweight/obese during the pandemic. Estimates on the full sample are likely biased, as they point towards an increased probability of male internet users being classified as overweight/obese during the pandemic, but do not take into account pre-pandemic BMI. Interactions of age and sex-specific internet use of model (2) are not significant.

In Table 5, we show the household fixed effects estimates of model (1), with binary depression as the dependent variable. Based on the estimates on the subsample of individuals who, within the household, are all either depressed or not depressed prior to the pandemic (utilising the threshold of 5/6 of the pre-pandemic EURO-D score for binary categorisation), internet use is, on average, not significant.[18]

In Table 6, we report the AMEs of internet use on depression, by sex and age, based on the estimates of model (2). According to the estimates on the subsample outlined above, among those who use the internet prior to the pandemic, females aged 65–70 are between 2.9 and 6.4 percentage points more likely to be depressed, males aged 65 are 4.5 percentage points more likely to be depressed, and females and males above the age of 80 are between 2.8 and 11.2 percentage points less likely to be depressed, during the pandemic. The estimates of the female-specific AMEs derived from the full sample are likely biased, as they fail to point towards an increased probability of depression among internet users aged 65 to 70.

[17] When not reported, results of the analyses are available upon request.

[18] It is important to recognise that the disparity in the number of observations for physical health measures compared to the mental health measures can be explained by our restriction of the full samples to individuals who fall into the same binary health-outcome categories prior to the pandemic, and so by the distribution of binary depression exhibiting a greater degree of skewness.

4.1.2. Secondary results and sensitivity analyses

In Appendix, we report the main results from our secondary and sensitivity analyses.

First, we show the household random effects estimates of model (1) and model (2), in Tables A.5–A.8. Overall, these estimates are biased, as they fail to account for pre-pandemic health statuses as well as for household-shared determinants of health outcomes, and suggest, on average, a protective effect of internet use on all health outcomes.

Second, we estimate model (1), with binary self-reported health as the dependent variable, on the subsample of 4,090 individuals who exhibit the same pre-pandemic self-reported health within the household, with now five health categories being utilised instead of two, specifically poor, fair, good, very good, and excellent. Our findings continue to indicate no significant association between internet use and binary self-reported health during the pandemic.

Third, we estimate model (1), with binary overweight/obesity as the dependent variable, on the subsample of 4,292 individuals who exhibit the same pre-pandemic BMI category within the household, with now four categories being utilised instead of two, specifically underweight, normal weight, overweight, and obese.[19] Our findings continue to indicate no significant association between internet use and binary overweight/obesity during the pandemic.

Fourth, we use the original cut-off point 3/4 for the diagnosis of depression based on the EURO-D score (Prince et al., 1999). The household fixed effects estimates of model (1) and the AMEs derived from the estimates of model (2) are shown in Tables A.9 and A.10, respectively. The estimates suggest that internet use has a detrimental effect on the mental health of females, on average, as well as on both females and males aged 65–70, while revealing no significant association for the oldest-old segment of the population.

Fifth, we estimate model (1) and model (2), using the EURO-D score measured in wave 9 as the dependent variable instead of binary depression, focusing on the subsample of 2,506 individuals who exhibit identical pre-pandemic EURO-D scores in the household. The household fixed effects estimates of model (1) and the AMEs by age and sex are shown in Tables A.11 and A.12, respectively. Male internet users exhibit, on average, EURO-D scores that are 0.19 points higher. Additionally, both female and male internet users aged 65 to 70, along with male internet users aged 75, exhibit EURO-D scores that are between 0.25 and 0.55 points higher than those of their age-matched peers who do not use the internet before the pandemic.

Sixth, we check if the household fixed effects estimates based on the linear probability models (1) and (2) are reliable and estimate Chamberlain's correlated random effects probit models, by controlling for the household-mean of the household-varying regressors (Wooldridge, 2010), and by including the country fixed effects, and compare the Chamberlain's AMEs to the estimates in Tables 3–6, finding no remarkable differences, aside from the absence of a significant association of internet use with depression in males aged 65. These results are shown in Tables A.13 and A.14.

Seventh, we investigate the association of internet use with categorical BMI (i.e., underweight, normal weight, overweight, obese) and categorical self-reported health (i.e., poor, fair, good, very good, excellent), during the pandemic. To do so, we estimate Chamberlain's correlated random effects ordered probit models, by controlling for the household mean of the household-varying regressors (Wooldridge, 2010) and by including the country fixed effects. This approach enables us to move beyond the simplified binary categorisation of overweight/obesity and self-reported health, allowing for dependence between household-shared characteristics and internet use, while focusing on categorical dependent variables. We find no significant association between internet use and categorical self-reported health, both in the original subsample of 6,466 individuals with identical binary pre-pandemic self-reported health and in the restricted subsample of 4,090 individuals with identical pre-pandemic categorical self-reported health described above. Similarly, we find no significant association between internet use and categorical BMI, both in the original subsample of 6,394 individuals with identical binary pre-pandemic overweight/obesity and in the restricted subsample of 4,292 individuals with identical pre-pandemic categorical BMI described above.

Eighth, we re-estimate all models concerning self-reported health, using the self-reported health data from wave 9 as the dependent variable, rather than the data from wave SCS2. Our findings continue to indicate no significant association between pre-pandemic internet use and self-reported health in the restricted samples, and a positive association, in both males and females, when pre-pandemic health is not accounted for and the full sample is used.

Finally, we employ the design weights provided by SHARE (in wave 8) and estimate model (1) and model (2) through weighted household fixed effects regressions. Certainly, the availability of sampling resources varies among SHARE countries, although the majority of these countries have access to population registers (Börsch-Supan et al., 2013). So, the sampled individuals of most SHARE countries are representative of the population of that country. Nevertheless, the probability of an individual being sampled varies from one country to another, indicating that certain countries may be overrepresented. Under these circumstances, by accounting for country fixed effects,[20] unweighted linear regressions might be the best choice, conditional on the conditional mean being correctly specified, as weighting might be unnecessary for consistency and harmful for precision (Solon et al., 2015). The weighted estimates reported in Tables A.15 and A.16 indicate conclusions that align closely with the primary findings derived from unweighted regressions. Specifically, they suggest that internet use has no significant impact on self-reported health and overweight/obesity during the pandemic and a detrimental effect on the mental health of females aged 65–70.

4.2. Pre-pandemic internet use, social ties, and telemedicine during the COVID-19 pandemic

4.2.1. Main results

In Table 7, we show the household fixed effects estimates of model (3). Comparing the estimates on the subsample of internet nonusers and on the subsample of internet users suggests that, as expected, the size of the social network increases the probability of accessing remote medical consultations for the former group only. Specifically, for internet nonusers, an additional person in the pre-pandemic social network is associated with 2.3 to 3.7 percentage points higher probability of accessing remote medical consultations during the COVID-19 pandemic.

4.2.2. Secondary results and sensitivity analyses

In Appendix, we report the main results from our secondary and sensitivity analyses.

First, in Table A.17, we report the household random effects estimates of model (3), which, again, appear to be biased.

Second, we estimate Chamberlain's correlated random effects probit models, by controlling for the household-mean of the household-varying regressors (Wooldridge, 2010), and by including the country fixed effects, and compare the AMEs to the estimates in Table 7, finding no difference. These results are shown in Table A.18.

Third, we perform additional analyses on the subsample of internet nonusers. First, we interact social network size with age and education, finding non-significant interactions. Then, we interact social network

[19] No underweight individuals, after this restriction, are included in the subsample, as there are no couples who are both underweight before the pandemic.

[20] As we do, indirectly, through the household fixed effects estimator.

size with pre-pandemic self-reported sadness/depression, estimating a marginally significant and stronger positive association between social network size and access to remote medical consultations in males who do not report being sad or depressed in wave 8. Then, we interact social network size with pre-pandemic self-reported health, finding a marginally significant and stronger positive association between social network size and access to remote medical consultations in females who report being in the tails of the health distribution (i.e., either poor or excellent health), in wave 8.

Finally, we estimate a Poisson household fixed effects regression,[21] with the number of remote medical consultations as the dependent variable. The natural logarithm of the number of months since the beginning of the pandemic until the time of the interview in wave SCS2 is included as the offset, with its coefficient fixed at 1. Due to the inclusion of the offset, we exclude from the controls the difference in months between the interview in wave 8 and the interview in wave SCS2. We report the estimated incidence rate ratios (IRRs) in Table A.19. We estimate, among the internet nonusers, an IRR of social network size in males of 1.09. Estimates on the subsample of internet users are not significant.

5. Discussion and conclusions

This paper investigates the association between pre-pandemic internet use and physical and mental health outcomes among the elderly population in Europe, during the COVID-19 pandemic. We estimate a series of household fixed effects regressions on outcome-specific samples of individuals, aged over 65, grouped into households consisting of more than one member. Nearly every household in our dataset is composed of married or cohabiting partners of opposite sex, with approximately 12% of these households also including other individuals who are not included in SHARE or do not fall within the 65+ age category.

We minimise the bias in the estimates by accounting for a rich set of household-varying controls, and for all the household-shared determinants of physical and mental health through the household fixed effects estimator. Moreover, we account for pre-pandemic health statuses and reverse causality, as we estimate the models on the subsample of individuals who, in the household, exhibit the same pre-pandemic health outcomes.

Our strategy for addressing reverse causality is based on the assumption that different health trajectories throughout life, experienced prior to the pre-pandemic period (i.e., before wave 8), did not significantly confound the relationship between internet use and health outcomes during the pandemic. In other words, we assume that, conditional on all household-shared characteristics and observed household-varying controls, and focusing solely on partners with identical pre-pandemic health outcomes within the household, the influence of health trajectories throughout life, leading up to the household-constant pre-pandemic health outcome, was negligible.[22]

On average, our estimates point towards a non-significant effect of pre-pandemic internet use on all health outcomes, during the pandemic. The association between pre-pandemic internet use and depression near the end of the pandemic strongly depended on the age-range: internet users in the age-range 65–70 were more likely to be depressed, while internet users in the age-range over 80 were less likely to be depressed, with stronger negative association as age increases. The findings regarding depression among internet users aged 65–70, particularly among females, are robust to several alternative models, specifications and estimators.

We employ similar models to investigate whether, among older internet nonusers, those with stronger social ties had higher probability of accessing remote medical consultations during the pandemic. As expected, the size of the social network was relevant only for those who did not use the internet before the pandemic. Pre-pandemic internet users likely already possessed the digital skills to navigate telemedicine platforms independently, and did not rely on external support to access remote consultations: as a result, the size of their social network was not influential. Among pre-pandemic internet nonusers, the association was stronger in males who, before the pandemic, were neither sad nor depressed and in females who, before the pandemic, had either poor or excellent health. Further research is needed to explore the mechanisms underlying these subgroup differences.

The main limitation of our results is that the household fixed effects estimates represent the population of older individuals who are married or cohabiting partners (with similar levels of pre-pandemic physical or mental health), while it is not clear to which extent the results can be generalised to unmarried, widowed, separated and divorced older people. Certainly, unmarried and divorced older individuals are recognised to experience poorer health outcomes (Robards et al., 2012), and this trend may have been enhanced in the context of the pandemic, when loneliness and social isolation were pronounced by the outbreak of COVID-19, although several studies have either found stable trajectories of loneliness, or greater risk of loneliness for younger rather than older individuals (Luchetti et al., 2020; Bu et al., 2020). However, it is generally acknowledged that adults living alone or suffering from chronic medical conditions did experience increased risk of being lonely (Bu et al., 2020; Elran-Barak and Mozeikov, 2020), which in turn could have led, as a result of that loneliness, to a decline in their self-assessed health, an increase in internet use, particularly in relation to social media platforms, and an increased perception of consuming more food (Elran-Barak and Mozeikov, 2020), suggesting a growing risk of elevated BMI.

Future research may explore the limitations regarding the generalisability of our findings to different segments of the elderly population by exploiting policies and initiatives implemented by EU and non-EU governments and institutions and aimed at boosting digital competencies or enhancing connectivity to the internet. Examples may include policies to lower WiFi-connection costs and increase download speed during the pandemic.

Another limitation of our study is that our empirical approach prevents us from investigating the relationship between internet use and BMI for individuals who were underweight before the pandemic, due to the absence of couples in the sample consisting of both underweight individuals. However, we do not consider this to be a major limitation, as only a small fraction of the overweight/obesity sample (0.72%) falls into the pre-pandemic underweight category.

From a methodological point of view, this research aims at providing novel contributions to the literature. The adoption of the household fixed effects estimator allows us to mitigate omitted variable bias. This is particularly important in the study of the association between health and internet use in old age, as multiple socio-demographic household-shared factors, which shape health inequalities, have been found to be also associated with internet use in old age. For instance, several studies have shown that internet users have, on average, higher socioeconomic status (König et al., 2018; Yu et al., 2017) and tend to live more often in urban or suburban areas (Sala et al., 2022). Similar factors are determinants of health in old age, as a vast literature (e.g., Friel and Marmot 2011) has shown differences by socioeconomic status in health and longevity, and links between urbanisation and worse mental health (Kovess-Masféty et al., 2005), but lower mortality risk (Cross et al., 2021), have been detected. Additionally, life-events such as marital status, the number of children and the loss of a child can all

[21] By conditioning on sn_i, $\mathbf{x}_i$, $\mathbf{z}_i$, and on the household fixed effects, overdispersion in the dependent variable is limited (Cameron and Trivedi, 2013).

[22] For instance, one household member has no history of depression prior to the pandemic, while their partner experienced depression at some point but had since recovered before the pandemic.

affect health status in later years (Grundy and Holt, 2000), and the presence and proximity of children may impact parental health (Van der Pers et al., 2015) and the use of the internet, particularly for communication (Mok et al., 2010).

The fact that partners living in the same household shared the same environment and very similar experiences during the pandemic, especially during the lockdowns, reinforces the suitability of the household fixed effects estimator. Indeed, the pandemic had the potential to exacerbate inequalities by socio-demographic status and ethnicity, among the old age population. Furthermore, the pandemic impacted disproportionately disadvantaged urban areas and neighbourhoods, particularly affecting the elderly residing in poor-quality housing (Buffel et al., 2023). As such, employing household fixed effect models allows taking into account this heterogeneity.

Fixed effects models appear to be underutilised in the literature when examining the relationship between internet use and health. Most of the papers that investigate the causal effect of internet use on health outcomes exploit exogenous variations in internet speed (Chen and Liu, 2022; Michelle et al., 2024) or instruments for high-speed internet access (Golin, 2022). The main reason may be that exploiting variations in internet use within the same individual over time may not effectively tackle the problem of reverse causality, unless it is combined with other econometric strategies. Our method of exploiting variations in the use of the internet within cohabiting partners, focusing solely on couples with identical pre-pandemic health levels, is justified primarily by the onset of the pandemic itself, allowing for a comparison of health statuses before and during this period. In the absence of the pandemic's influence, our approach would lack robust justification.

In our models, we do not control for who tested positive for, or exhibited symptoms of, COVID-19. Although these variables are recorded in SHARE, the sample size is insufficient to draw meaningful conclusions. Omitting these controls could constitute a problem in models that fail to account for all household-shared determinants of health during the pandemic. One reason for this is that the internet served as a resource for information aimed at preventing the transmission of the virus. Consequently, the association, or absence thereof, that we observe between internet use and health during the pandemic may, to some extent, reflect a correlation between internet use and the probability of contracting the virus. Additionally, not controlling for vaccine uptake against COVID-19 may confound the association, as internet users could have been misled by conspiracy theories proliferating online that discouraged vaccination (Valla et al., 2024).

We do not consider overlooking such variables in our models to be an issue for several reasons. First, if an individual contracted the SARS-CoV-2 virus, there was a remarkable probability that other household members would also become infected (Madewell et al., 2022). Second, as mentioned above, partners living in the same household shared the same environment and very similar experiences during the pandemic, especially during the lockdowns, when the probability of contracting the virus was higher and the expected consequences were more severe. Consequently, if only one individual in the household contracted the virus, chances are that it happened at random. Therefore, the fixed effects estimates would be unaffected, unless the individual in question was the only one in the household who was not fully vaccinated.

If pre-pandemic internet use and vaccine uptake were correlated, the latter was likely to play the role of a mediator rather than a confounding factor, as pre-pandemic internet use was generally unaffected by future events, more so because the anti-vaccination network and movement were much weaker before the pandemic (Lenti et al., 2023). If vaccine uptake acted as a mediator between pre-pandemic internet use and health outcomes during the pandemic, our findings may be relevant solely to the context of the pandemic. This is due to the increased exposure of internet users to conspiracy theories (De Coninck et al., 2021), which may have played a role in the rise of depressive symptoms (Debski et al., 2022), and reduced the probability of individuals receiving the vaccine, ultimately leading to worse health outcomes for those affected. While we acknowledge the value of investigating the mediating role of vaccine uptake, this is left for future research.

The results of this study suggest some unexpected patterns regarding the impact of internet use on mental health outcomes, among older adults, during the pandemic. Among younger seniors (aged 65–70), increased internet use was associated with heightened depressive symptoms, contrary to the general expectation that digital engagement might alleviate loneliness and depressive states by fostering social connections. This paradoxical outcome might be explained by the nature of internet use among these individuals. Studies have shown that, while internet use for communication can reduce loneliness, usage focused on information searching, particularly related to health, can exacerbate anxiety and depression due to information overload and exposure to distressing content (Wallinheimo and Evans, 2021, 2022). Additionally, the forced shift to online platforms due to lockdowns might have increased stress among those less familiar with digital technologies, thereby worsening their mental health (Kung and Steptoe, 2023).

Indeed, studies indicate that the intense reliance on digital platforms for information and communication during the pandemic created a fertile ground for anxiety and emotional distress. Gao et al. (2020) and Chao et al. (2020) observed that exposure to alarming and contradictory content via social media and digital news channels was significantly associated with worsened mental health outcomes, particularly due to the amplification of fear and uncertainty. Furthermore, Wheaton et al. (2021) highlighted the role of emotional contagion through social media, which compounded anxiety and depressive symptoms as individuals were exposed to collective fears and stress about the pandemic.

This phenomenon aligns with the broader issue of the "infodemic", a term used to describe the overwhelming spread of often misleading information during the pandemic. Cinelli et al. (2020) and Shoib et al. (2022) emphasise that the sheer volume of information, combined with the difficulty of discerning credible sources, likely led to cognitive overload and heightened stress, exacerbating pre-existing vulnerabilities in mental health. Similarly, the phenomenon of "doomscrolling", where individuals compulsively consume negative online content, further illustrates how internet use can deepen feelings of helplessness and despair (Price et al., 2022), so that news avoidance was adopted as a strategy to reduce mental distress during the pandemic (Mannell and Meese, 2022).

In addition to the psychological burden of excessive information, younger seniors may have faced unique challenges related to the use of digital technologies. The concept of "technostress" (Tarafdar et al., 2011) describes the strain induced by adapting to new technologies, especially when these technologies are required for essential activities. For many individuals in this age group, the abrupt transition to digital reliance during the pandemic might have intensified feelings of frustration and inadequacy, contributing to poor mental health (Camacho and Barrios, 2022).

Lastly, the simultaneous use of multiple platforms for communication, news, and social interaction, commonly referred to as "digital multitasking", can further impair cognitive and emotional regulation. Ophir et al. (2009) and Hasan (2024) demonstrated that multitasking across digital media not only decreases cognitive control but also increases hyperactivity and stress, which are risk factors for anxiety and depression.

These considerations suggest that the relationship between internet use and mental health is not inherently positive or negative but multifaceted and contingent on usage patterns and individual circumstances. The younger seniors who engaged more actively with digital platforms during the pandemic might have experienced these negative effects more acutely, explaining the unexpected increase in depressive symptoms detected. These findings are consistent with broader discussions regarding the internet's dual role as a source of connection and a potential driver of polarisation, loneliness, and mental health challenges. While internet use can foster social bonds and facilitate access to information (Chen and Schulz, 2016; Nedeljko et al., 2021), its impact is highly context-dependent, influenced by individual user behaviour, content exposure, and digital literacy. A more nuanced understanding of these conflicting dynamics is essential to contextualise the observed increase in depressive symptoms within this demographic.

Among the oldest seniors (aged over 80), a decrease in depression with increased internet use was observed. This could be attributed to the fact that, for this age group, internet use primarily functions as a crucial tool for maintaining social ties and accessing supportive communities (Sims et al., 2017). Consequently, this engagement provides emotional benefits and reduces feelings of isolation (Kung and Steptoe, 2023; Wallinheimo and Evans, 2021). Moreover, a greater percentage of the oldest demographic uses the internet for "health-related tasks" in comparison to younger age groups (Friemel, 2016), signalling that the oldest-old demographic may exhibit a greater propensity than younger seniors to leveraging technologies aimed at improving health and wellbeing. The disparity between the two age groups underscores the importance of considering the context and manner of internet use when evaluating its psychological impact.

Our findings underscore the importance of recognising the heterogeneous nature of old age. It is indeed beneficial to transcend the general 65+ classification and to differentiate between the youngest-old and the oldest-old (aged over 80), commonly known as the "fourth age" (Laslett, 1994). This distinction is particularly significant in the context of technology adoption, where notable differences exist across age groups within the older population (Hargittai and Dobransky, 2017). Also, evidence on differences by sex in the effect of internet use on health are particularly relevant in light of the mixed evidence on differences by sex in technology adoption (Hunsaker and Hargittai, 2018; Sala et al., 2022).

With respect to the external validity of our findings beyond the 2020–2023 sanitary emergency, on one hand, we acknowledge that factors specific to the pandemic may have influenced the physical and mental health of older adults throughout this period. Consequently, general policy recommendations may face limitations due to the characteristics of the pandemic, thereby requiring a cautious approach for their execution. On the other hand, we view the pandemic as an interesting case study; indeed, the pandemic has accelerated the (ongoing) digitalisation of society, and, hence, the requirement to use digital technologies to perform day-to-day activities (Hantrais et al., 2021). For example, during the pandemic older adults needed to rely on the internet for intergenerational communication, accessing services, purchasing goods, and exercising. As such, the pandemic mimics a situation in which older adults are forced to connect through the internet for day-to-day activities, circumstances that closely resemble the "new normal" of an increasingly digital world. Therefore, we believe that our findings hold relevance beyond the immediate context of the pandemic, offering important insights into the challenges and policy implications of digital inclusion for older populations in the years to come.

Policy makers and health professionals should work towards promoting digital literacy programmes that incorporate peer-to-peer training and intergenerational support. Such efforts aim to encourage older individuals, particularly those in the younger segments of the elderly population, to develop the digital skills necessary to effectively harness technology for improved health outcomes. This includes improving their ability to access medical services online and evaluate the credibility of information available on the internet. Moreover, policy efforts should focus on reversing the negative effects of social media use on mental health, such as the harmful effects of social comparison. This could be achieved by promoting balanced digital engagement, encouraging users to integrate online activities with meaningful offline interactions. Policies should aim to prevent over-reliance on online communities, which can potentially weaken offline social ties, and discourage excessive allocation of time to passive online engagement at the expense of mentally enriching and physically stimulating offline activities.

To conclude, while internet use has the potential to offer significant benefits to older adults, its impact, particularly on mental health, is complex and multifaceted. The context of use, individual familiarity with technology, and the specific purposes for which the internet is utilised play crucial roles in determining its effects on mental health. Therefore, future interventions should be tailored to address these nuances, promoting beneficial uses of digital technology while mitigating its adverse effects.

Adopting a multi-dimensional approach to the study of inequalities – as advocated by recent literature (Anand et al., 2020) but rarely implemented empirically – further research may assess how digital inequalities, health inequalities and inequalities in social capital interrelate with other forms of inequalities. For instance, it seems crucial to examine the relationship between digital and labour market inequalities, focusing on the challenges senior workers with limited digital skills face in remote working or online job searching. This comprehensive approach can provide a deeper understanding of how various forms of inequality intersect and amplify each other, ultimately informing more effective policy interventions.

CRediT authorship contribution statement

Gianmaria Niccodemi: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Alessandra Gaia:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Funding acquisition, Conceptualization. **Mino Novello:** Writing – review & editing, Writing – original draft, Data curation. **David Consolazio:** Writing – review & editing, Writing – original draft, Supervision.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the first author used *Ahrefs* in order to improve the readability of a few paragraphs. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. Additional tables

See Tables A.1–A.19.

Table A.1
Household composition, by outcome-specific sample and age-range.

	Sample			
	Self-reported health	Overweight/obesity	Depression	Remote medical consultations
Full sample	9,794	10,454	10,330	9,430
Partners (%)	99.66%	99.71%	99.71%	99.65%
Individuals sharing HH with one person (%)	87.38%	88.83%	88.65%	87.51%
Individuals sharing HH with two+ people (%)	12.62%	11.17%	11.35%	12.49%
Individuals who are 80+ years of age	1,606	1,592	1,523	1,514
Partner in HH (%)	99.75%	99.87%	99.87%	99.74%
Individuals sharing HH with one person (%)	89.79%	91.83%	91.86%	90.03%
Individuals sharing HH with two+ people (%)	10.21%	8.17%	8.14%	9.97%

"Full sample" denotes the number of individuals in each outcome-specific sample. "Partners" refers to the percentage of individuals, whether from the full outcome-specific sample or specifically those aged 80 and above, who are either married or cohabiting partners. "Individuals sharing HH with one person" refers to the percentage of individuals, whether from the full outcome-specific sample or specifically those aged 80 and above, who share the household with one person only, with both individuals being included in the outcome-specific sample. "Individuals sharing HH with two+ people" refers to the percentage of individuals, whether from the full outcome-specific sample or specifically those aged 80 and above, who share the household with additional individuals who are either not included in SHARE, are not 65+ or are excluded from the outcome-specific sample.

Table A.2
Distribution of categorical variables, by outcome-specific restricted sample.

	Restricted sample		
	Self-reported health	Overweight/obesity	Depression
Self-reported health (wave SCS2):			
Poor	8.91%		
Fair	30.82%		
Good	40.77%		
Very good	15.40%		
Excellent	4.10%		
BMI - categories (wave 9):			
Underweight		0.81%	
Normal weight		26.32%	
Overweight		45.28%	
Obese		27.59%	
Depression (wave 9)			6.74%
Access to remote medical consultations (wave SCS2)			
Internet use	52.49%	52.67%	56.50%
Female	50.00%	49.98%	50.00%
Education:			
Low	33.37%	33.47%	31.11%
Medium	41.35%	42.66%	42.75%
High	25.27%	23.87%	26.14%
Employment status:			
Retired	88.12%	89.02%	89.13%
Employed	3.17%	2.85%	3.30%
Unemployed	0.09%	0.09%	0.08%
Disabled	0.40%	0.39%	0.30%
Home maker	7.73%	7.16%	6.71%
Other	0.48%	0.48%	0.49%
Observations	6,466	6,394	9,226

Unless otherwise specified, variables are observed in wave 8.

Table A.3
Descriptive statistics of non-categorical variables, by outcome-specific restricted sample.

	Observations	Mean	Standard deviation	Minimum	Maximum
Self-reported health restricted sample:					
Age (wave SCS2)	6,466	74.88	5.80	66	96
Wellbeing	6,466	37.74	6.24	12	48
Difference in months (wave 8/SCS2)	6,466	18.00	1.40	15	22
Overweight/obesity restricted sample:					
BMI (wave 9)	6,394	27.76	4.60	12.60	58.59
Age (wave 9)	6,394	75.29	5.62	66	102
Wellbeing	6,394	37.75	5.94	12	48
Difference in months (wave 8/9)	6,394	25.51	2.68	19	34
Depression restricted sample:					
EURO-D score	9,226	2.11	2.00	0	12
Age (wave 9)	9,226	75.21	5.59	66	96
Wellbeing	9,226	38.48	5.68	12	48
Difference in months (wave 8/9)	9,226	25.48	2.67	19	34

Unless otherwise specified, variables are observed in wave 8.

Table A.4
Travel restrictions due to COVID-19, by wave periods and key dates.

SHARE country	Wave SCS2		Wave 9			SHARE country	Wave SCS2		Wave 9		
	01-06-21	31-08-21	01-10-21	31-03-22	31-09-22		01-06-21	31-08-21	01-10-21	31-03-22	31-09-22
Austria	D	D	D	B	A	Israel	E	E	E	B	A
Belgium	D	D	D	C	A	Italy	D	C	C	B	A
Bulgaria	D	D	D	B	A	Latvia	D	C	C	B	A
Croatia	D	B	B	B	A	Lithuania	B	B	B	B	A
Cyprus	C	B	B	B	A	Luxembourg	D	D	D	B	A
Czech Republic	D	C	C	B	A	Malta	D	D	D	D	A
Denmark	D	C	C	A	A	Netherlands	D	D	D	A	A
Estonia	B	B	B	B	A	Poland	B	B	B	A	A
Finland	D	B	B	B	A	Slovakia	C	B	B	B	A
France	D	B	B	B	A	Slovenia	B	B	B	A	A
Germany	D	B	B	B	A	Spain	D	C	C	B	B
Greece	D	D	D	B	A	Sweden	B	B	B	B	A
Hungary	C	B	B	A	A	Switzerland	D	B	B	A	A

A: no restrictions; B: screening arrivals; C: quarantine arrivals from some or all regions; D: ban arrivals from some regions; E: ban on all regions or total border closure. Source: ourworldindata.org.

Table A.5
Household random effects estimates on self-reported health, by sample.

	$y = 1$ if good+ self-reported health	
	Full sample	Constant pre-pandemic health in HH
Internet use × female	0.083^{***}	0.076^{***}
	(0.012)	(0.020)
Internet use × male	0.072^{***}	0.064^{***}
	(0.014)	(0.016)
Female	−0.011	−0.022
	(0.014)	(0.018)
Age	-0.010^{***}	-0.011^{***}
	(0.001)	(0.001)
Wellbeing	0.022^{***}	0.022^{***}
	(0.001)	(0.001)
Difference in months (wave 8/SCS2)	-0.006^{*}	-0.008^{*}
	(0.003)	(0.004)
Education:		
Medium	0.022	0.020
	(0.014)	(0.019)
High	0.060^{***}	0.066^{***}
	(0.014)	(0.016)
Employment status:		
Employed	0.050	0.046
	(0.033)	(0.035)
Unemployed	0.414^{***}	0.448^{***}
	(0.078)	(0.058)
Disabled	-0.192^{***}	-0.175^{**}
	(0.056)	(0.069)
Home maker	0.009	0.006
	(0.017)	(0.022)
Other	−0.034	−0.054
	(0.065)	(0.083)
Country fixed effects	Yes	Yes
Year and month fixed effects	Yes	Yes
Test sex-specific internet use: p-value	0.470	0.586
Number of observations	9,794	6,466
Number of couples	4,897	3,233

"Constant pre-pandemic health in HH" denotes the sample of individuals who, within the household, exhibit the same category of binary pre-pandemic self-reported health (either poor/fair or good/very good/excellent). "Test sex-specific internet use" is the test on whether the sex-specific coefficients of internet use are different. The standard errors (in parentheses) are clustered at the country level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.6
Household random effects estimates on overweight/obesity, by sample.

	$y = 1$ if overweight/obese	
	Full sample	Constant pre-pandemic overweight/obesity in HH
Internet use × female	-0.046^{***}	-0.033^{**}
	(0.016)	(0.013)
Internet use × male	0.022^{*}	−0.019
	(0.012)	(0.014)
Female	-0.048^{**}	−0.013
	(0.024)	(0.014)
Age	-0.008^{***}	-0.008^{***}
	(0.001)	(0.001)
Wellbeing	-0.003^{***}	−0.002
	(0.001)	(0.001)
Difference in months (wave 8/9)	0.007^{*}	0.008
	(0.004)	(0.006)
Education:		
Medium	-0.032^{***}	−0.015
	(0.012)	(0.010)
High	-0.107^{***}	-0.086^{***}
	(0.013)	(0.012)
Employment status:		
Employed	−0.004	0.008
	(0.025)	(0.029)
Unemployed	−0.131	0.099
	(0.111)	(0.127)
Disabled	−0.059	0.059
	(0.077)	(0.106)
Home maker	-0.036^{**}	−0.014
	(0.014)	(0.012)
Other	−0.069	−0.095
	(0.073)	(0.101)
Country fixed effects	Yes	Yes
Year and month fixed effects	Yes	Yes
Test sex-specific internet use: p-value	0.001	0.470
Number of observations	10,454	6,394
Number of couples	5,227	3,197

"Constant pre-pandemic overweight/obesity in HH" denotes the sample of individuals who, within the household, exhibit the same category of binary pre-pandemic BMI (either overweight/obese or not overweight/obese) in the household. "Test sex-specific internet use" is the test on whether the sex-specific coefficients of internet use are different. The standard errors (in parentheses) are clustered at the country level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.7
Household random effects estimates on depression, by sample.

	$y = 1$ if 6+ EURO-D score	
	Full sample	Constant pre-pandemic depression in HH
Internet use × female	−0.016**	−0.007
	(0.008)	(0.006)
Internet use × male	−0.020	−0.020*
	(0.013)	(0.011)
Female	0.037***	0.021*
	(0.013)	(0.011)
Age	0.003***	0.002***
	(0.001)	(0.001)
Wellbeing	−0.014***	−0.010***
	(0.001)	(0.001)
Difference in months (wave 8/9)	0.002	−0.001
	(0.003)	(0.002)
Education:		
Medium	−0.009	−0.015**
	(0.009)	(0.008)
High	−0.015*	−0.014*
	(0.008)	(0.008)
Employment status:		
Employed	−0.003	−0.001
	(0.017)	(0.016)
Unemployed	0.099	0.073
	(0.096)	(0.125)
Disabled	0.068	0.046
	(0.062)	(0.068)
Home maker	0.036**	0.014
	(0.017)	(0.010)
Other	0.083	0.041
	(0.066)	(0.066)
Country fixed effects	Yes	Yes
Year and month fixed effects	Yes	Yes
Test sex-specific internet use:		
p-value	0.822	0.315
Number of observations	10,330	9,226
Number of couples	5,165	4,613

"Constant pre-pandemic depression in HH" denotes the sample of individuals who, before the pandemic, are all either depressed or not depressed in the household, based on the 5/6 EURO-D threshold. "Test sex-specific internet use" is the test on whether the sex-specific coefficients of internet use are different. The standard errors (in parentheses) are clustered at the country level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.8
Household random effects average marginal effects of internet use on depression, by sex, age and sample.

	$y = 1$ if 6+ EURO-D score			
	Full sample		Constant pre-pandemic depression in HH	
	Female	Male	Female	Male
Age 65	0.017	0.025	0.041**	0.018
	(0.021)	(0.015)	(0.019)	(0.017)
70	−0.001	0.005	0.014	0.002
	(0.013)	(0.013)	(0.011)	(0.012)
75	−0.019**	−0.014	−0.013**	−0.014
	(0.009)	(0.012)	(0.006)	(0.010)
80	−0.036***	−0.033**	−0.039***	−0.030**
	(0.014)	(0.015)	(0.011)	(0.014)
85	−0.054**	−0.052***	−0.066***	−0.046**
	(0.022)	(0.019)	(0.019)	(0.020)
90	−0.071**	−0.072***	−0.093***	−0.062**
	(0.031)	(0.024)	(0.028)	(0.026)
Test internet use × female × age:				
p-value	0.073		0.003	
Test internet use × male × age:				
p-value		0.001		0.038
Number of observations	10,330		9,226	
Number of couples	5,165		4,613	

"Constant pre-pandemic depression in HH" denotes the sample of individuals who, before the pandemic, are all either depressed or not depressed in the household, based on the 5/6 EURO-D threshold. "Test internet use × female × age" and "Test internet use × male × age" are the tests on whether the interaction terms between internet use, sex (female and male, respectively) and age are significant. The standard errors (in parentheses) are clustered at the country level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.9
Household fixed effects estimates on depression — alternative cut-off point 3/4.

	$y = 1$ if 4+ EURO-D score
	Constant pre-pandemic depression in HH
Internet use × female	0.031*
	(0.018)
Internet use × male	0.019
	(0.018)
Female	0.078***
	(0.015)
Age	0.008**
	(0.003)
Wellbeing	−0.013***
	(0.002)
Difference in months (wave 8/SCS2-9)	−0.008
	(0.031)
Education:	
Medium	−0.008
	(0.017)
High	−0.027
	(0.020)
Employment status:	
Employed	0.028
	(0.035)
Unemployed	0.017
	(0.170)
Disabled	−0.095
	(0.123)
Home maker	−0.030
	(0.021)
Other	0.099
	(0.072)
Country fixed effects	Not identified
Year and month fixed effects	Yes
Test sex-specific internet use: p-value	0.518
Number of observations	7,550
Number of couples	3,775

"Constant pre-pandemic depression in HH" denotes the sample of individuals who, before the pandemic, are all either depressed or not depressed in the household, based on the 3/4 EURO-D threshold. "Test sex-specific internet use" is the test on whether the sex-specific coefficients of internet use are different. The standard errors (in parentheses) are clustered at the country level. The standard errors and the p-values are computed with the cluster-robust CR2 estimator (Bell and McCaffrey, 2002) and the t-distribution with the Imbens and Kolesar (2016) degrees of freedom, respectively.
$^{*} p < 0.1$, $^{**} p < 0.05$, $^{***} p < 0.01$.

Table A.10
Household fixed effects average marginal effects, by sex and age, of internet use on depression — alternative cut-off point 3/4.

	$y = 1$ if 4+ EURO-D score	
	Constant pre-pandemic depression in HH	
	Female	Male
Age 65	0.063*	0.082**
	(0.036)	(0.039)
70	0.046**	0.055**
	(0.022)	(0.023)
75	0.030	0.027
	(0.018)	(0.017)
80	0.014	−0.001
	(0.029)	(0.027)
85	−0.003	−0.029
	(0.044)	(0.044)
90	−0.019	−0.057
	(0.061)	(0.062)
Test internet use × female × age: p-value	0.378	
Test internet use × male × age: p-value		0.156
Number of observations	7,550	
Number of couples	3,775	

"Constant pre-pandemic depression in HH" denotes the sample of individuals who, before the pandemic, are all either depressed or not depressed in the household, based on the 3/4 EURO-D threshold. "Test internet use × female × age" and "Test internet use × male × age" are the tests on whether the interaction terms between internet use, sex (female and male, respectively) and age are significant. The standard errors (in parentheses) are clustered at the country level. The standard errors and the p-values are computed with the cluster-robust CR2 estimator (Bell and McCaffrey, 2002) and the t-distribution with the Imbens and Kolesar (2016) degrees of freedom, respectively.
$^{*} p < 0.1$, $^{**} p < 0.05$, $^{***} p < 0.01$.

Table A.11
Household fixed effects estimates on EURO-D score for depression.

	y is the EURO-D score
	Constant pre-pandemic EURO-D in HH
Internet use × female	0.210
	(0.129)
Internet use × male	0.188^{*}
	(0.102)
Female	0.350^{**}
	(0.127)
Age	0.067^{**}
	(0.024)
Wellbeing	-0.040^{***}
	(0.012)
Difference in months (wave 8/SCS2-9)	−0.287
	(0.251)
Education:	
Medium	-0.234^{*}
	(0.118)
High	−0.272
	(0.157)
Employment status:	
Employed	0.015
	(0.193)
Unemployed	2.738
	(3.453)
Disabled	−0.134
	(0.889)
Home maker	−0.190
	(0.166)
Other	0.737
	(0.884)
Country fixed effects	Not identified
Year and month fixed effects	Yes
Test sex-specific internet use:	
p-value	0.869
Number of observations	2,506
Number of couples	1,253

“Constant pre-pandemic EURO-D in HH” denotes the sample of individuals who, before the pandemic, exhibit the same EURO-D score in the household. “Test sex-specific internet use” is the test on whether the sex-specific coefficients of internet use are different. The standard errors (in parentheses) are clustered at the country level. The standard errors and the p-values are computed with the cluster-robust CR2 estimator (Bell and McCaffrey, 2002) and the t-distribution with the Imbens and Kolesar (2016) degrees of freedom, respectively. $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

Table A.12
Household fixed effects average marginal effects, by sex and age, of internet use on EURO-D score for depression.

	y is the EURO-D score	
	Constant pre-pandemic EURO-D in HH	
	Female	Male
Age 65	0.385^{**}	0.551^{*}
	(0.194)	(0.290)
70	0.267^{**}	0.402^{**}
	(0.114)	(0.187)
75	0.149	0.253^{**}
	(0.140)	(0.111)
80	0.030	0.103
	(0.239)	(0.123)
85	−0.088	−0.046
	(0.356)	(0.210)
90	−0.206	−0.196
	(0.476)	(0.314)
Test internet use × female × age:		
p-value	0.356	
Test internet use × male × age:		
p-value		0.204
Number of observations	2,506	
Number of observations	1,253	

“Constant pre-pandemic EURO-D in HH” denotes the sample of individuals who, before the pandemic, exhibit the same EURO-D score in the household. “Test internet use × female × age” and “Test internet use × male × age” are the tests on whether the interaction terms between internet use, sex (female and male, respectively) and age are significant. The standard errors (in parentheses) are clustered at the country level. The standard errors and the p-values are computed with the cluster-robust CR2 estimator (Bell and McCaffrey, 2002) and the t-distribution with the Imbens and Kolesar (2016) degrees of freedom, respectively. $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

Table A.13
Average marginal effects of internet use on binary health outcomes based on Chamberlain’s correlated random effects probit estimates, by sex.

	Constant pre-pandemic health outcomes in HH					
	Self-reported health		Overweight/obesity		Depression	
	Female	Male	Female	Male	Female	Male
AME Internet use	0.028	0.010	−0.023	−0.005	0.011	−0.015
	(0.028)	(0.028)	(0.018)	(0.015)	(0.010)	(0.010)
Number of observations	6,466		6,394		9,226	
Number of couples	3,233		3,197		4,613	

The Chamberlain’s correlated random effects probit model includes and interacts pre-pandemic internet use and female, and controls for age, wellbeing, difference in months between wave 8 and either wave SCS2 or 9 (depending on the outcome), education, employment status, country fixed effects and the fixed effects for the year and month of the interview, as well as for the household mean of the regressors. Self-reported health during the COVID-19 pandemic is a binary variable equal to 0 if self-reported health is poor or fair, and equal to 1 if it is good or above. Overweight/obesity is a binary variable equal to 1 if the individual, during the pandemic, is overweight or obese, and equal to 0 otherwise. Depression is a binary variable equal to 1 if the EURO-D score, during the pandemic, is equal to or greater than 6, and equal to 0 otherwise. “Constant pre-pandemic health outcomes in HH” denotes the sample of individuals who, within the household, exhibit the same category of binary pre-pandemic health outcome (either poor/fair or good/very good/excellent self-reported health; either overweight/obese or not overweight/obese; either depressed or not depressed, based on the 5/6 EURO-D threshold). The standard errors (in parentheses) are clustered at the country level. $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

Table A.14
Average marginal effects of internet use on depression based on Chamberlain's correlated random effects probit estimates, by sex and age.

	Constant pre-pandemic depression in HH	
	Female	Male
Age 65	0.052***	0.006
	(0.016)	(0.010)
70	0.033***	0.001
	(0.011)	(0.010)
75	0.006	−0.008
	(0.010)	(0.010)
80	−0.030*	−0.022*
	(0.018)	(0.012)
85	−0.075**	−0.042*
	(0.035)	(0.021)
90	−0.131**	−0.069*
	(0.063)	(0.038)
Number of observations	9,226	
Number of couples	4,613	

The Chamberlain's correlated random effects probit model includes and interacts pre-pandemic internet use, female and age, and controls for wellbeing, difference in months between wave 8 and wave 9, education, employment status, country fixed effects and the fixed effects for the year and month of the interview, as well as for the household mean of the regressors. Depression is a binary variable equal to 1 if the EURO-D score, during the COVID-19 pandemic, is equal to or greater than 6, and equal to 0 otherwise. "Constant pre-pandemic depression in HH" denotes the sample of individuals who, before the pandemic, are all either depressed or not depressed in the household, based on the 5/6 EURO-D threshold. The standard errors (in parentheses) are clustered at the country level. * $p < 0.1$,** $p < 0.05$,*** $p < 0.01$.

Table A.15
Weighted household FE estimates on health outcomes.

	Constant pre-pandemic health outcomes in HH		
	Self-reported health	Overweight/obesity	Depression
Internet use × female	0.014	−0.011	0.006
	(0.019)	(0.018)	(0.010)
Internet use × male	−0.035	0.003	−0.023
	(0.033)	(0.026)	(0.026)
Female	−0.018	−0.005	0.011
	(0.019)	(0.013)	(0.018)
Age	0.000	−0.001	0.002
	(0.004)	(0.002)	(0.002)
Wellbeing	0.016***	0.000	−0.009***
	(0.004)	(0.001)	(0.003)
Difference in months (wave 8/SCS2-9)	0.053	0.023	0.009
	(0.055)	(0.044)	(0.042)
Education:			
Medium	−0.026	−0.019	−0.024
	(0.034)	(0.017)	(0.017)
High	−0.003	−0.026	−0.021
	(0.032)	(0.023)	(0.022)
Employment status:			
Employed	−0.015	0.118	−0.036
	(0.050)	(0.094)	(0.046)
Unemployed	0.500*	0.009	0.262
	(0.120)	(0.026)	(0.220)
Disabled	0.013	0.031	−0.012
	(0.095)	(0.251)	(0.058)
Home maker	−0.009	0.031*	−0.008
	(0.041)	(0.013)	(0.012)
Other	0.051	−0.054	−0.050
	(0.181)	(0.059)	(0.056)
Country fixed effects	Not identified	Not identified	Not identified
Year and month fixed effects	Yes	Yes	Yes
Test sex-specific internet use: *p*-value	0.105	0.519	0.231
Number of observations	6,466	6,394	9,226
Number of couples	3,233	3,197	4,613

Self-reported health during the COVID-19 pandemic is a binary variable equal to 0 if self-reported health is poor or fair, and equal to 1 if it is good or above. Overweight/obesity is a binary variable equal to 1 if the individual, during the pandemic, is overweight or obese, and equal to 0 otherwise. Depression is a binary variable equal to 1 if the EURO-D score, during the pandemic, is equal to or greater than 6, and equal to 0 otherwise. "Constant pre-pandemic health outcomes in HH" denotes the sample of individuals who, within the household, exhibit the same category of binary pre-pandemic health outcome (either poor/fair or good/very good/excellent self-reported health; either overweight/obese or not overweight/obese; either depressed or not depressed, based on the 5/6 EURO-D threshold). "Test sex-specific internet use" is the test on whether the sex-specific coefficients of internet use are different. The standard errors (in parentheses) are clustered at the country level. The standard errors and the p-values are computed with the cluster-robust CR2 estimator (Bell and McCaffrey, 2002) and the t-distribution with the Imbens and Kolesar (2016) degrees of freedom, respectively. * $p < 0.1$,** $p < 0.05$,*** $p < 0.01$.

Table A.16
Weighted household fixed effects average marginal effects of internet use on depression, by sex and age.

	Constant pre-pandemic depression in HH	
	Female	Male
Age 65	0.061***	0.036
	(0.016)	(0.023)
70	0.031***	0.012
	(0.009)	(0.017)
75	0.001	−0.012
	(0.015)	(0.020)
80	−0.029	−0.037
	(0.026)	(0.031)
85	−0.059	−0.061
	(0.038)	(0.044)
90	−0.089*	−0.085
	(0.051)	(0.057)
Test internet use × female × age:		
p-value	0.042	
Test internet use × male × age:		
p-value		0.123
Number of observations	9,226	
Number of couples	4,613	

Depression is a binary variable equal to 1 if the EURO-D score, during the COVID-19 pandemic, is equal to or greater than 6, and equal to 0 otherwise. "Constant pre-pandemic depression in HH" denotes the sample of individuals who, before the pandemic, are all either depressed or not depressed in the household, based on the 5/6 EURO-D threshold. "Test internet use × female × age" and "Test internet use × male × age" are the tests on whether the interaction terms between internet use, sex (female and male, respectively) and age are significant. The standard errors (in parentheses) are clustered at the country level. The standard errors and the p-values are computed with the cluster-robust CR2 estimator (Bell and McCaffrey, 2002) and the t-distribution with the Imbens and Kolesar (2016) degrees of freedom, respectively.
$^{*}p < 0.1$,$^{**}p < 0.05$,$^{***}p < 0.01$.

Table A.17
Household random effects estimates on access to remote medical consultations, by sample.

	$y = 1$ if 1+ remote medical consultations		
	Full sample	Internet nonusers	Internet users
Social network size × female	0.010**	0.005	0.010*
	(0.005)	(0.008)	(0.006)
Social network size × male	0.013**	0.016*	0.010
	(0.006)	(0.009)	(0.006)
Female	0.011	0.051*	−0.012
	(0.017)	(0.029)	(0.030)
Age	−0.001	0.001	−0.002
	(0.001)	(0.001)	(0.001)
Wellbeing	0.001	0.001	0.000
	(0.001)	(0.002)	(0.002)
Difference in months			
(wave 8/SCS2)	−0.006	−0.009	−0.007
	(0.006)	(0.011)	(0.008)
Education:			
Medium	0.028**	0.031*	0.015
	(0.011)	(0.017)	(0.019)
High	0.057***	0.027	0.054**
	(0.013)	(0.037)	(0.024)
Employment status:			
Employed	−0.062**	−0.128**	−0.059
	(0.026)	(0.053)	(0.036)
Unemployed	−0.021	−0.136*	0.343***
	(0.166)	(0.071)	(0.029)
Disabled	0.046	0.027	0.110
	(0.059)	(0.077)	(0.121)
Home maker	0.017	0.011	0.035
	(0.024)	(0.033)	(0.041)
Other	−0.049	−0.071	0.042
	(0.058)	(0.106)	(0.114)
Self-reported health			
(wave 8):			
Fair	−0.027	−0.043	0.017
	(0.024)	(0.027)	(0.041)
Good	−0.039	−0.071**	0.040
	(0.025)	(0.031)	(0.041)
Very good	−0.025	−0.020	0.028
	(0.031)	(0.050)	(0.045)
Excellent	−0.110***	−0.236***	−0.035
	(0.042)	(0.090)	(0.064)
Self-reported health			
(wave SCS2):			
Fair	−0.010	0.025	−0.024
	(0.020)	(0.031)	(0.037)
Good	−0.073***	−0.073*	−0.096**
	(0.024)	(0.043)	(0.038)
Very good	−0.124***	−0.133***	−0.151***
	(0.027)	(0.038)	(0.046)
Excellent	−0.168***	−0.087	−0.206***
	(0.029)	(0.062)	(0.043)
Self-reported sadness/depression			
(wave 8)	0.030**	0.019	0.045**
	(0.012)	(0.016)	(0.019)
Self-reported sadness/depression			
(wave SCS2)	0.051***	0.072***	0.049***
	(0.014)	(0.017)	(0.019)
Country fixed effects	Yes	Yes	Yes
Year and month fixed effects	Yes	Yes	Yes
Test sex-specific social network size:			
p-value	0.579	0.174	0.935
Number of observations	9,430	3,274	3,678
Number of couples	4,715	1,637	1,839

"Internet nonusers" denotes the sample of individuals who, before the pandemic (in wave 8), report not using the internet in the 7 days preceding the interview. "Internet users" denotes the sample of individuals who, before the pandemic (in wave 8), report using the internet at least once in the 7 days preceding the interview. "Test sex-specific social network size" is the test on whether the sex-specific coefficients of social network size are different. The standard errors (in parentheses) are clustered at the country level.
$^{*}p < 0.1$,$^{**}p < 0.05$,$^{***}p < 0.01$.

Table A.18
Average marginal effects of social network size on access to remote medical consultation based on Chamberlain's correlated random effects probit estimates, by sex and sample.

	Full sample		Internet nonusers		Internet users	
	Female	Male	Female	Male	Female	Male
AME social network size	0.016***	0.018***	0.023**	0.039***	0.009	0.008
	(0.005)	(0.005)	(0.010)	(0.008)	(0.008)	(0.007)
Number of observations	9,430		3,274		3,678	
Number of couples	4,715		1,637		1,839	

The Chamberlain's correlated random effects probit model includes and interacts pre-pandemic social network size and female, and controls for age, wellbeing, difference in months between wave 8 and wave SCS2, education, employment status, self-reported health and sadness/depression (wave 8 and SCS2), country fixed effects and the fixed effects for the year and month of the interview, as well as for the household mean of the regressors. Access to remote medical consultations during the COVID-19 pandemic is a binary variable equal to 1 if the number of remote medical consultations is 1 or higher, and equal to 0 otherwise. "Internet nonusers" denotes the sample of individuals who, before the pandemic (in wave 8), report not using the internet in the 7 days preceding the interview. "Internet users" denotes the sample of individuals who, before the pandemic (in wave 8), report using the internet at least once in the 7 days preceding the interview. The standard errors (in parentheses) are clustered at the country level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.19
Incidence rate ratios based on Poisson household fixed effects estimates on number of remote medical consultations, by sample.

	y is the number of remote medical consultations		
	Full sample	Internet nonusers	Internet users
Social network size × female	1.011	1.039	1.040
	(0.032)	(0.032)	(0.052)
Social network size × male	0.996	1.088**	0.989
	(0.041)	(0.036)	(0.062)
Female	0.961	1.242***	0.768
	(0.121)	(0.097)	(0.157)
Age	0.995	1.020**	0.963
	(0.014)	(0.009)	(0.025)
Wellbeing	1.008	0.999	1.017
	(0.007)	(0.008)	(0.015)
Education:			
Medium	0.955	1.058	0.786
	(0.080)	(0.074)	(0.181)
High	0.931	1.105	0.724
	(0.095)	(0.134)	(0.184)
Employment status:			
Employed	0.831	0.797	0.734
	(0.119)	(0.167)	(0.140)
Unemployed	2.502	0.961	6.249***
	(1.413)	(0.152)	(2.538)
Disabled	1.232	1.047	2.572
	(0.240)	(0.163)	(1.708)
Home maker	0.914	0.913	1.144
	(0.068)	(0.073)	(0.225)
Other	1.437	2.170	0.584
	(0.533)	(1.088)	(0.226)
Self-reported health (wave 8):			
Fair	1.214	0.955	1.644
	(0.200)	(0.085)	(0.584)
Good	1.009	0.813*	1.318
	(0.147)	(0.091)	(0.433)
Very good	0.997	0.946	1.216
	(0.167)	(0.153)	(0.447)
Excellent	0.677*	0.611*	0.779
	(0.160)	(0.160)	(0.336)
Self-reported health (wave SCS2):			
Fair	0.908	0.873	1.189
	(0.105)	(0.079)	(0.311)
Good	0.632***	0.671***	0.741
	(0.066)	(0.078)	(0.180)
Very good	0.423***	0.434***	0.528**
	(0.058)	(0.077)	(0.144)
Excellent	0.301***	0.507**	0.271***
	(0.078)	(0.151)	(0.104)
Self-reported sadness/depression (wave 8)	1.210	1.257***	1.210
	(0.150)	(0.084)	(0.213)
Self-reported sadness/depression (wave SCS2)	1.080	1.124*	0.965
	(0.068)	(0.072)	(0.165)
Country fixed effects	Not identified	Not identified	Not identified
Year and month fixed effects	Yes	Yes	Yes
Test sex-specific social network size: p-value	0.696	0.050	0.454
Number of observations	9,430	3,274	3,678
Number of couples	4,715	1,637	1,839

"Internet nonusers" denotes the sample of individuals who, before the COVID-19 pandemic (in wave 8), report not using the internet in the 7 days preceding the interview. "Internet users" denotes the sample of individuals who, before the pandemic (in wave 8), report using the internet at least once in the 7 days preceding the interview. "Test sex-specific social network size" is the test on whether the sex-specific coefficients of social network size are different. The offset is the natural logarithm of the number of months from the beginning of the pandemic to the time of the interview conducted in wave SCS2 and its coefficient is fixed at 1. The standard errors (in parentheses) are clustered at the household level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Data availability

SHARE data are accessible via the SHARE Research Data Center website, upon request.

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