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Research Article

Internet and mental health during the COVID-19 pandemic: evidence from the UK

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Abstract

With the COVID-19 pandemic, the internet has become a key player in the daily lives of most people. We investigate the relationship between mental health and internet use frequency and purpose, 6 months after the first lockdown in the UK, in September 2020. Using data from the UK Household Longitudinal Study on the 12-item General Health Questionnaire and the internet use module, and controlling for sociodemographic characteristics and personality traits, we find that older individuals (aged 59 years or above) have a lower internet use frequency (twice a day or less). Younger women use the internet for social purposes more than men do, while younger men use the internet for leisure-and-learning purposes more than women and older men do. Interestingly, high internet use is a protective factor for social dysfunction among younger women, but a risk factor for psychological distress among younger men. While leisure-and-learning purpose is a protective factor for social dysfunction among younger women, it is a risk factor for social dysfunction among younger men. Finally, loneliness seems to play a role: higher internet frequency use is a stronger protective factor for social dysfunction among younger women who feel lonelier but a stronger risk factor for mental health among younger men who feel lonelier.

Keywords: PCA, EFA, regression, leisure-and-learning, social dysfunction, psychological distress, loneliness, GHQ-12

Introduction

The COVID-19 pandemic and the measures to contain the transmission of the virus have transformed our daily routines. For many people, the internet has become a central part of their lives, from online education to working-from-home. At the same time, the mental well-being of the population has been negatively affected by the pandemic (Proto & Quintana-Domeque, 2021, Quintana-Domeque & Proto, 2022), and this deterioration has been heterogeneous among demographic groups, with younger adults and women being disproportionately affected (Banks & Xu, 2020). Our focus in this paper is on the link between the internet and mental health during the COVID-19 pandemic, with a particular focus on whether such a relationship varies between younger and older adults and between men and women.

We use data from the UK Household Longitudinal Study (UKHLS) to answer three questions. First, do age and gender predict internet use frequency and purpose? Second, do internet use frequency and purpose predict mental health? Third, do internet use frequency and purpose predict mental health differently by age and gender? In order to answer these questions, we use three different measures of mental health [Likert 12-item General Health Questionnaire (GHQ-12) score (0–36), psychological distress score and social dysfunction score], a measure of internet use frequency [low (twice a day or less) vs. high (more than twice a day)], three scores of internet use purpose (functional, social and leisure-and-learning) and a host of control variables, including personality traits, whose relevance in understanding the consequences of the COVID-19 pandemic on mental health has been recently shown (Proto & Zhang, 2021).

Our multiple regression analysis reveals several findings. In terms of frequency of use, older individuals use the internet less frequently. Younger women use the internet for social purposes more than men do, while younger men use the internet for leisure-and-learning purposes more than women and older men do. In terms of mental health, internet use is a protective factor for social dysfunction among younger women but a risk factor for psychological distress among younger men. Moreover, while using the internet for leisure-and-learning purposes is a protective factor for social dysfunction among younger women, it is a risk factor for social dysfunction among younger men.

The relationship between the internet and mental health has been studied previously in economics and psychology. Golin (2022), who provides a detailed summary of the literature on the relationship between internet and mental health, investigates the causal effect of broadband internet access on the mental health of adults aged 17–59 years in Germany. Inspired by the work of Falck *et al.* (2014), her identification strategy to deal with both unobservable determinants of mental health and behaviours and reverse causality is based on a natural experiment that exploits technological features of the German telecommunication network. Her findings suggest that broadband internet has negative effects on women's mental health but not on men's. To the best of our knowledge, Golin (2022) is the first study to provide convincing evidence of a causal relationship of internet (broadband access) on validated measures of mental health among adults.

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We depart from Golin (2022) in four different ways. First, the populations under study are different. Our focus is the UK, not Germany, and our sample encompasses individuals aged 23–93 years, rather than 17–59 years. Second, our analysis focuses on the COVID-19 pandemic period, a period when the internet has become a key player in the daily lives of most people. Third, as Golin (2022) acknowledges, the effect of the internet use on mental health depends on the type of activities that are carried out online, but her paper cannot speak about that. Our study instead relies on rich internet data on both use frequency and purposes in September 2020, after contributing suggested content that became the internet use module of the September 2020 COVID-19 wave study (pp. 123–127, https://www.understandingsociety.ac.uk/sites/default/files/downloads/documentation/covid-19/questionnaires/wave-5/W5-covid-19-questionnaire.pdf). Finally, our cross-sectional study is mainly descriptive, while Golin (2022) uses time variation and focuses on causality by exploiting technological features of the German telecommunication network. Nevertheless, we investigate the plausibility of our analysis capturing the causal effect of internet use on mental health by using Oster (2019)'s bounds analysis. Our Oster (2019)'s bounds analysis suggests that the estimated associations between internet use frequency and mental health are unlikely to be driven by the correlation between internet use frequency and unobservable factors. Moreover, most of our findings are robust to adjusting for multiple testing. What can explain the heterogeneous patterns by age and gender? We find that, among young women, internet use may be a protective factor for social dysfunction the lonelier they feel. However, among young men, we find that, if anything, those who feel lonelier and use internet more frequently are at a higher risk of worse mental health. While we acknowledge the exploratory and descriptive nature of the loneliness analysis, we hope it fosters new hypotheses for future research.

Data sources, variables and descriptive statistics

Our main data source is the UKHLS. (University of Essex, Institute for Social and Economic Research, NatCen Social Research, Kantar Public (2020); University of Essex, Institute for Social and Economic Research (2020); University of Essex, Institute for Social and Economic Research (2021). Understanding Society data are available through the UK Data Service. Researchers who would like to use Understanding Society need to register with the UK Data Service before being allowed to apply for or download datasets. More information: https://www.understandingsociety.ac.uk/documentation/access-data.) The UKHLS, also known as Understanding Society, is a large national probability-based household panel survey, involving over 100 000 individuals in 40 000 households in the UK since wave 1 (2009–2011) (Institute for Social and Economic Research, 2020). The UKHLS provides high-quality longitudinal data on subjects such as social life, education, employment, personality, health and well-being. All members of households aged 16+ years who participated in waves 8 or 9 of the UKHLS main survey were invited to participate in the COVID-19 study. The COVID-19 study is an integral part of the UKHLS, which is a panel study on experiences and how the UK population reacts to the COVID-19 pandemic (Institute for Social and Economic Research, 2021). The first wave of the COVID-19 survey was in April 2020 and the last one in September 2021.

All analyses are conducted using Stata (version 17), and we account for survey design and sample weights using the `svyset` command in Stata, so that we adjust for unequal selection probabilities and differential non-response to ensure the results are representative of the UK population. (Note that the COVID-19 survey weights map to the main wave 9 population. It provides estimates that are representative of the population of individuals (16+ years) resident in private households in the UK at the time of wave 9.)

The key variables in our analysis can be classified into three groups: internet use (frequency and purpose), mental health and other explanatory variables (including sociodemographic and personality characteristics).

Internet use frequency and internet use purpose

All waves of the COVID-19 study collect information on household access to the internet from home. Moreover, we contributed suggested content that became the internet use module of the September 2020 COVID-19 wave study. The special Internet Use Module collects detailed internet use information, including frequency of using the internet and frequency of 10 different online activities (browsing websites, email, looking at social media, posting on social media, online buying, online banking, gaming, streaming videos, streaming music and education). For this reason, the September 2020 COVID-19 wave study is our main data resource for internet usage. We use two types of internet measures: internet use frequency and internet use purpose.

Internet use frequency. Respondents were asked how often they use the internet for their personal use, frequency from 'Almost all of the time' to 'Never use' (https://www.understandingsociety.ac.uk/documentation/covid-19/dataset-documentation/variable/netpusenew). The frequency of using the internet is categorized into a binary variable to represent low (twice a day or less) and high levels (more than twice a day) of internet use. (Although data on internet use frequency were collected in previous waves, different categories were used. In particular, while the September 2020 wave distinguishes intensity of internet use within a day (i.e. Almost all the time, Several times a day, Once or twice a day), previous waves did not distinguish the intensity within a day (i.e. Every day, https://www.understandingsociety.ac.uk/documentation/mainstage/dataset-documentation/variable/netpuse).)

Internet use purpose. Respondents were asked how often they use the internet for personal use to do a specific online activity. There are 10 online activities in the questionnaire, including browsing websites, email, looking at social media, posting on social media, online buying, online banking, gaming, streaming videos, streaming music and education (pp. 123–127, https://www.understandingsociety.ac.uk/sites/default/files/downloads/documentation/covid-19/questionnaires/wave-5/W5-covid-19-questionnaire.pdf). Each activity is re-coded from 6 (every day) to 1 (never), where higher scores indicate personal internet use for the activity at the frequency level. (Information on internet use purpose was not available in pre-pandemic waves of the UKHLS (https://www.understandingsociety.ac.uk/documentation/mainstage/dataset-documentation?search_api_views_fulltext=internet).) Several online activities are highly correlated with each other. For instance, the correlations between browsing websites and email, looking at social media and posting on social media and streaming videos and streaming music are 0.735, 0.603 and 0.698, respectively. We use principal component analysis (PCA) with Promax rotation to extract the important information from 10 online activities and reduce the dimensionality of the data set (Abdi & Williams, 2010, Bro & Smilde, 2014). Respondents in the September survey with valid answers on ten online activities are used for PCA.

Table 1. Descriptive statistics of internet use purpose scores

Variable	N	Mean	Std.Dev.	Min	Max
Functional purpose score	12 811	0.00	1.60	−5.64	2.45
Leisure-and-learning purpose score	12 811	0.00	1.45	−2.19	3.42
Social purpose score	12 811	0.00	1.30	−2.73	2.37

Note: This table shows descriptive statistics of internet use purposes of 12 811 respondents with valid answers on 10 online activity questions in the September survey.

The PCA indicated a three-component solution, explaining 64% of the total variance in online activities (component 1 eigenvalue = 4.18, component 2 eigenvalue = 1.20, component 3 eigenvalue = 1.03). Variables loading heavily on the first component (26.6% of the variance) are browsing websites, email, online banking and online buying. Variables loading heavily on the second component (20.8% of the variance) are streaming videos, streaming music and online education. Variables loading heavily on the third component (17.4% of the variance) are looking at social media, posting on social media and gaming.

We label the components 'Functional purpose', 'Leisure-and-learning purpose' and 'Social purpose', respectively, and use them as a measurement of respondents' internet use purposes (see PCA and the results in Appendix A). Table 1 provides the descriptive statistics of the internet purposes scores. Higher scores indicate higher internet use frequency for that purpose. Scores are standardized in the final sample.

Mental health metrics

The GHQ-12 is included in every wave of the UKHLS main survey and COVID-19 survey. The GHQ-12 is a reliable and valid self-administered questionnaire designed to identify minor psychiatric disorders in community samples (Goldberg, 1988, Goldberg et al., 1997), a widely accepted indicator of mental well-being (Bro & Smilde, 2014), and has been used to assess the impact of the COVID-19 pandemic on mental health in the UK (Banks & Xu, 2020, Proto & Quintana-Domeque, 2021, Proto & Zhang, 2021, Quintana-Domeque & Proto, 2022). The 12 items collect information about how individuals feel about themselves on concentration, anxiety-based insomnia, capability in coping, ability to enjoy day-to-day activities, confidence, being under strain, feeling depressed and unhappiness, among others over the last few weeks on a four-point Likert scale (https://doi.org/10.1371/journal.pone.0244419.s001).

We use three measures based on the GHQ-12. The first measure is the Likert GHQ-12, a continuous Likert scale that sums the 12 items of the GHQ. Each item scores from 0 (better than usual) to 3 (much worse than usual), and the Likert GHQ-12 score ranges from 0 (best mental wellbeing) to 36 (worst mental wellbeing).

The other two measures exploit the potential multidimensional properties of the GHQ-12 score (Graetz, 1991, Griffith & Jones, 2019, Romppel et al., 2013). We follow the literature using exploratory factor analysis (EFA) with Varimax rotation (Williams et al., 2010) to identify dimensions of the GHQ-12 in the September survey. Varimax rotation produces factor structures that are uncorrelated and simplifies the interpretation of the factors by minimizing the number of variables that have high loadings on each factor (Williams et al., 2010). A total of 12 419 respondents in the September survey with valid answers on the GHQ-12 questionnaire are used for EFA. The EFA yielded a two-factor solution, explaining 73.73% of the total variance in items (factor 1 eigenvalue = 7.67 and factor 2 eigenvalue = 1.17). We label the factors psychological distress and social dysfunction, respectively (see EFA and the results in Appendix B).

The psychological distress score is related to anxiety and depression; more precisely, anxiety-based insomnia (item 2 of the GHQ-12), under strain (item 5), problem overcoming difficulties (item 6), depression (item 9), lose confidence (item 10) and believe worthless (item 11). The social dysfunction score is related to the ability to perform daily activities and to cope with everyday problems; more precisely, concentration (item 1 of the GHQ-12), playing a useful role (item 3), decision making (item 4), ability to enjoy day-to-day activities (item 7), face up to problems (item 8) and unhappiness (item 12). Table 2 provides the descriptive statistics of the psychological distress and social dysfunction scores. Higher scores indicate higher level of psychological distress or social dysfunction. Scores are standardized in the final sample.

Other explanatory variables

We use the following set of (additional) explanatory variables: age, female (=1 if female, =0 if male), ethnic minority (=1 if Black, Asian or other ethnic minority, = 0 if White British), education (measured in 2017–19), marital status, household size, employment status, household income, health status, COVID-19 symptoms, risky behaviours (smoking and drinking), physical exercise, geographical location, pre-pandemic mental well-being (measured in 2017–19), mental well-being in July 2020 and personality traits (measured in 2011–13). Table C1 in Appendix C contains the definition of each variable.

In order to use all this information, we match wave 3 (2011–13), wave 9 (2017–19), the July 2020 wave and the September 2020 wave and end up with a sample of 6589 individuals aged 23–93 years (5980 of them have non-zero cross-sectional sample weights in the September 2020 wave). The original sample size with information on the GHQ-12 is 10 267 (and with information on personality traits is 8589–8590), while the final sample size with information on all the relevant (including control) variables is 5980. Thus, the final sample represents 58% (70%) of the original sample. Table D1 in Appendix D reveals no differences between the original and the final samples in terms of internet use frequency, the fraction of men and women, the fraction of individuals who have/had COVID-19 symptoms, the percentage of individuals who drink heavily, the fraction of individuals who do regular exercise, and the big five personality traits. However, we find statistically differences at the 5% or lower significance level in terms of mental health, age, ethnicity, education, marital status, employment, income and smoking status. (Specifically, participants in our final matched sample have (on average) better mental health (GHQ12: 11.85 vs. 12.07), are 4.4 years older on average than those in the original sample, are 5 pp less likely to be Black, Asian or from any other ethnic minority, are 5 pp more likely to have a higher education degree, are 7 pp more likely to live with a partner, are 1 pp more likely to be employed and are 1 pp less likely to be smokers.)

Table 2. Descriptive statistics of psychological distress and social dysfunction scores

	N	Mean	Std.Dev.	Min	Max
Psychological distress score	12 419	–0.001	0.963	–2.731	3.897
Social dysfunction score	12 419	–0.003	0.942	–3.998	4.828

Note: This table shows descriptive statistics of two extracted factors of the GHQ-12 of 12 419 respondents with valid answers on GHQ-12 questionnaire in the September survey.

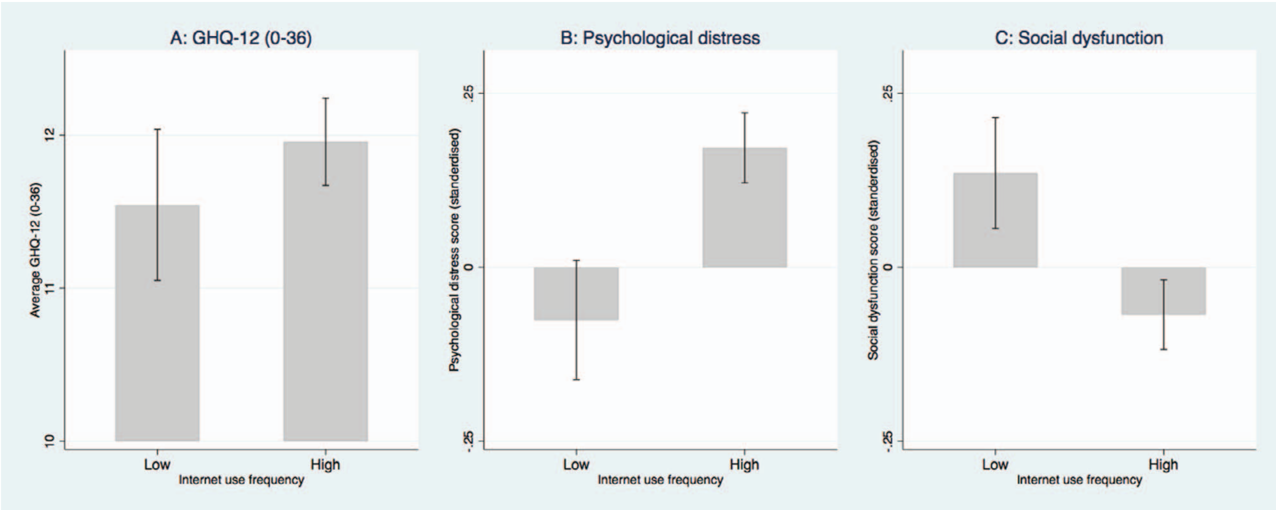

Figure 1. Mental health metrics by internet use frequency

Descriptive statistics

Table E1 in Appendix E provides a description of the average characteristics of the individuals in our final sample. The average age is 54.65 (SD=14.66): 53.8% of them are women, 91.6% are White British, 60.0% of them are employed and 47.2% have a higher education degree. In terms of mental health and internet use, the average GHQ-12 score is 11.85 (5.56) and 74% of individuals use the internet more than twice a day.

In Fig. 1, we plot the average mental health metrics by internet use frequency. Individuals who report a high internet use frequency (more than twice a day) tend to report a larger GHQ-12 score (11.96, 95% CI: 11.67, 12.24) than individuals reporting a low internet use frequency (11.54, 95% CI: 11.05, 12.04). While this difference is not significant, individuals reporting a low internet use frequency tend to significantly exhibit a lower psychological distress score but perform worse in terms of the social dysfunction score.

Figure 2 plots average mental health metrics by different levels of the functional purpose score [low (< 50%, below the median score) vs. high (≥ 50%, above the median score)]. There is a positive gradient between the average psychological distress score and functional purpose score and a negative gradient between the average social dysfunction score and functional purpose score. Similar qualitative gradients are observed when plotting the average psychological distress and social dysfunction scores against leisure-and-learning (Fig. 3) and social (Fig. 4) purposes scores.

Regression analysis

In this section, we conduct a regression analysis to investigate: (i) whether age and gender predict internet use frequency and internet use purpose, (ii) whether internet use frequency and internet use purposes predict mental health and (iii) whether such predictability varies by age and gender. We classify respondents whose age is equal or larger than the median age of the sample (59-year-old) as older respondents; otherwise, we classify them as younger respondents. We run four types of regressions.

First, to investigate whether age and gender predict internet use frequency, we run several versions of the following linear regression:

$$I_{it} = a_0 + a_1 F_i + a_2 O_i + a_3 (F_i \times O_i) + a_4 X_{it} + a_5 X_{it-s} + e_{it}, \qquad (1)$$

where $I_{it} = 1$ if the individual uses internet more than twice a day in September 2020, = 0 else; $F_i = 1$ if the individual is a female, = 0 else; $O_i = 1$ if the individual is 59 years old or more, = 0 else; X_{it} is a set of control variables measured contemporaneously (e.g. health status, geographical location); X_{it-s} is a set of control variables measured at $t-s$ (e.g. education (measured in 2017–19), personality traits (measured in 2011–13), pre- pandemic mental well-being (measured in 2017–19), mental well-being in July 2020) and e_{it} is a regression residual. Given the binary nature of the outcome variable, we also run a non-linear regression version of (1), a logistic regression.

Second, to investigate whether age and gender predict internet use purpose, we run several versions of the following linear regression:

$$IP^j_{it} = b^j_0 + b^j_1 F_i + b^j_2 O_i + b^j_3 (F_i \times O_i) + b^j_4 X_{it} + b^j_5 X_{it-s} + r^j_{it}, \qquad (2)$$

for $j = \{F, LL, S\}$, where IP^F_{it} is the individual functional purpose score, IP^{LL}_{it} is the individual leisure-and-learning purpose score and IP^S_{it} is the individual social purpose score, and all scores refer to September 2020.

Third, to investigate whether internet use frequency predict mental health, we run several versions of the following linear

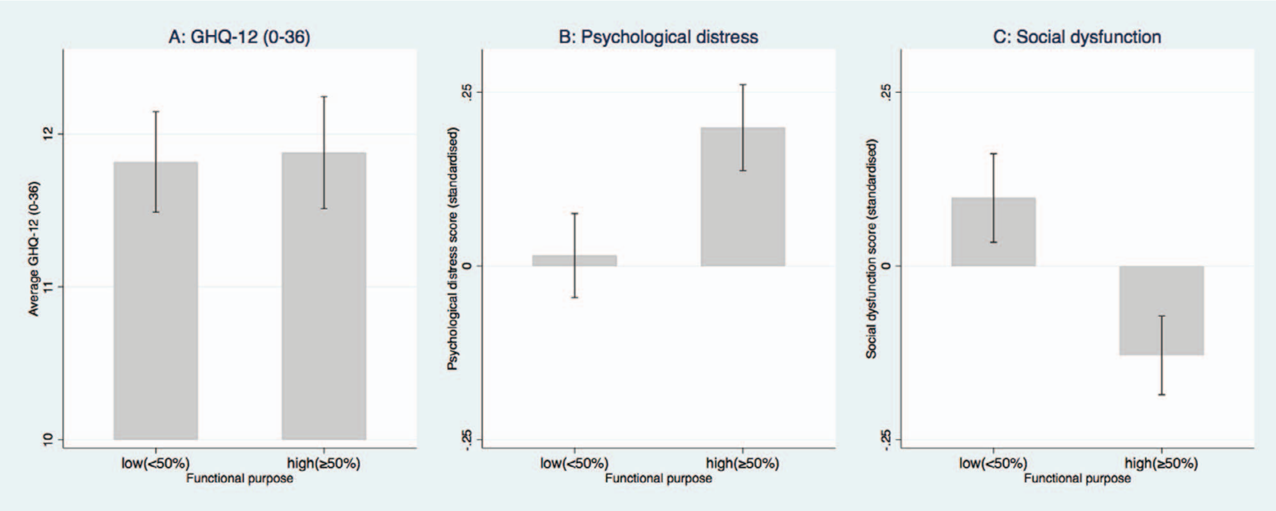

Figure 2. Mental health metrics by functional purpose use of the internet

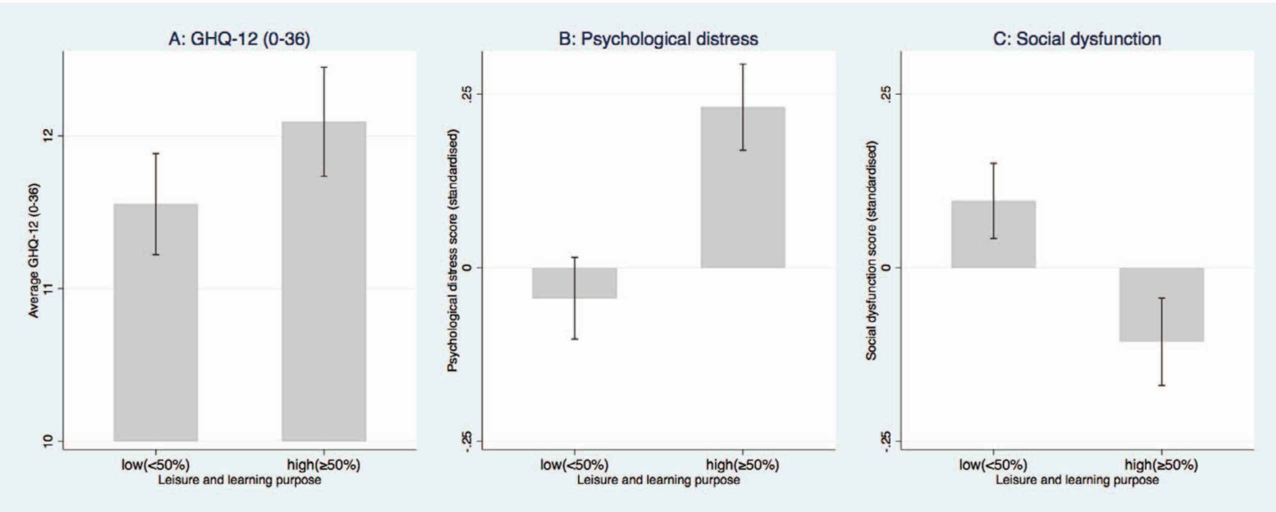

Figure 3. Mental health metrics by leisure-and-learning purpose use of the internet

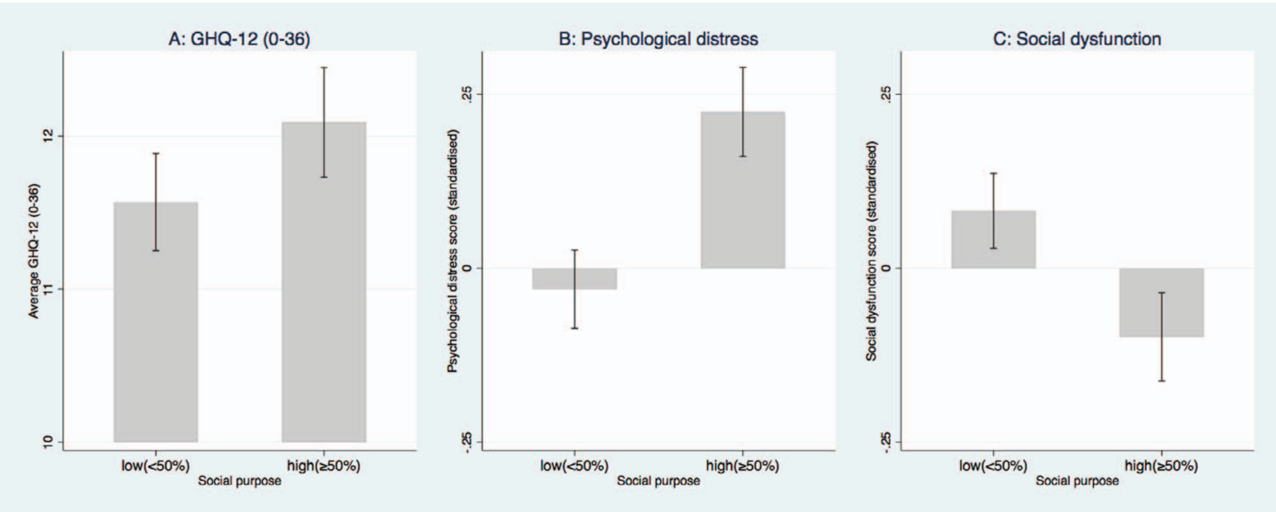

Figure 4. Mental health metrics by social purpose use of the internet

regression:

$$MH^j_{it} = c^j_0 + c^j_1 I_{it} + c^j_2 Age_i + c^j_3 Age^2_i + c^j_4 F_i + c^j_5 X_{it} + c^j_6 X_{it-s} + u^j_{it}, \quad (3)$$

for $j = \{GHQ-12, PD, SD\}$, where MH^{GHQ-12}_{it} is the individual GHQ-12 (0–36) score, MH^{PD}_{it} is the individual psychological distress score and MH^{SD}_{it} is the individual social dysfunction score, and all scores refer to September 2020.

Fourth, to investigate whether internet use purposes predict mental health, we run several versions of the following linear regression:

$$MH^j_{it} = d^j_0 + d^j_1 IP^F_{it} + d^j_2 IP^{LL}_{it} + d^j_3 IP^S_{it} + d^j_4 Age_i + d^j_5 Age^2_i + d^j_6 F_i + d^j_7 X_{it} + d^j_8 X_{it-s} + v^j_{it}. \quad (4)$$

In addition, to investigate whether such predictability varies by age and gender, we run regressions (3) and (4), without F_i and Age^2_i, separately for younger (aged <59 years) women, older (aged ≥59 years) women, younger men and older men and display the main findings of such heterogeneity analysis graphically.

Clarification We want to highlight that we use data on internet use and mental health from the September 2020 wave, which is the only wave having detailed internet use information. While we could theoretically predict mental health in the next wave, i.e. November 2020, it is important to note that the second lockdown came into force in England on the 5 November 2020, and the November 2020 wave collected data from the 24–30 November 2020, i.e. during the second lockdown. This shock is likely to impact both mental health and internet use, and it may also impact the way internet affects mental health. More importantly, the interaction effect is likely to be different for people under different circumstances (which may be unobservable too). Therefore, the estimated association between internet use in September 2020 and mental health in November 2020 is likely to capture different factors (some of them unobservable). Second, our regressions include as control variables lagged mental health [mental health at $t-1$ (July 2020) and mental health in the pre-pandemic period (2017–19)], so that we are using longitudinal, not just cross-sectional, information. Thus, the focus of our analysis is on the relationship between internet use and mental health at time t (September 2020), conditional or not on lagged mental health [at $t-1$ (July 2020) and before the pandemic (2017–19)].

Do age and gender predict internet use frequency and purpose?

In Table 3, we investigate whether age and gender predict internet use frequency. The table displays the regression results of a logit (panel A) and a linear probability model (panel B) of internet use frequency (1 if high use (more than twice a day) vs. 0 if low use (twice a day or less)). There is no significant difference between female and male in the internet use frequency. For older individuals (≥ 59 years), the odds of high use vs. low use are 0.32 times lower than for younger individuals (< 59 years), given the other variables are held constant. Hence, older individuals have a lower internet use frequency, which is consistent with previous studies (Lee *et al.*, 2011, Schehl *et al.*, 2019). Panel B shows that older individuals are between 30 percentage points (no controls, Column 2) and 20 percentage points (full set of controls, Column 4) less likely to frequently use the internet than younger ones. Moreover, we can see that older females are between 32 percentage points (Column 3) and 24 percentage points (Column 4) less likely than younger females to frequently use the internet. Table S1 in the Supplementary Material displays the estimates for all the control variables in Column (4).

We re-ran the regressions in Table 3 using a comparable definition of internet use frequency for the same individuals, before (2017–19) and during the pandemic (September 2020), in Tables S2 and S3 in the Supplementary Material. (The comparable definition of internet use = 1 if every day (before the pandemic), or almost all the time, several times a day or once or twice a day (during the pandemic) and = 0 else. Note that we compare the coefficients of the determinants (age and gender) without controls, since some of the controls are COVID-19-specific (e.g. indicator of whether the individual 'Has/ Had COVID-19 symptoms'). However, for the pandemic period, we also add control variables (Column 4 in Table S3), so that the estimates for Table 3 using two definitions of internet use frequency can be compared for the same pandemic period.) If we compare the estimates from Table S2 with those from Table S3 (i.e. comparing estimates based on the same definition of the outcome variable but different time periods), we can conclude the findings are qualitatively and quantitatively virtually the same. If we compare the estimates from Table S3 with those from Table 3 (i.e. comparing estimates based on different definitions of the outcome variable but the same time period), we can conclude that the findings are qualitatively identical and quantitatively very similar.

We then investigate whether age and gender predict internet purposes by means of linear regression. Given the other variables are held constant, Table 4 Panel A shows that the functional purpose score is 0.12 standard deviations larger among younger females than among younger males, 0.42 standard deviations smaller among older males than among younger males and 0.77 standard deviations smaller among older females than among younger females. Also, Table 4 Panel B shows that the leisure-and-learning purpose score is 0.44 standard deviations smaller among younger females than among younger males, 0.92 standard deviations smaller among older males than among younger males and 0.74 standard deviations smaller among older females than among younger females, given the other variables are held constant. Finally, Table 4 Panel C shows that the social purpose score is 0.12 standard deviations larger among younger females than among younger males, 0.55 standard deviations smaller among older males than among younger males and 0.53 standard deviations smaller among older females than among younger females, given the other variables are held constant. Table S4 in the Supplementary Material displays the estimates for all the control variables in Column (4).

Our analysis reveals that younger women use the internet for social purposes more than men do, while younger men use the internet for leisure-and-learning purposes more than women and older men do. Gender differences in the way internet is used have been reported previously (Jackson *et al.*, 2001). Females are more likely to engage in social online activities, while males use the internet more for entertainment activities (Chen *et al.*, 2017, Dufour *et al.*, 2016, Joiner *et al.*, 2012, Lemenager *et al.*, 2021). That men and women have different motivations and preferences regarding internet use and purpose (Weiser, 2000) might be indeed a reflection of gender differences in the wider society (Joiner *et al.*, 2012).

Do internet use frequency and purpose predict mental health?

In Table 5, we show the relationship between mental health metrics (GHQ-12 in panel A, psychological distress in panel B, social

Table 3. Do age and gender predict internet high use frequency?

	(1)	(2)	(3)	(4)
Panel A. Logit	Odds ratio	Odds ratio	Odds ratio	Odds ratio
Female	0.893		0.856	0.889
	[0.739,1.079]		[0.610,1.200]	[0.631,1.253]
Age ≥ 59 years		0.209***	0.218***	0.321***
		[0.170,0.258]	[0.158,0.301]	[0.223,0.462]
Female × Age ≥ 59 years			0.906	0.916
			[0.603,1.362]	[0.621,1.351]
Panel B. LPM	Coef.	Coef.	Coef.	Coef.
Female	–0.022		–0.018	–0.011
	[–0.058,0.015]		[–0.058,0.021]	[–0.051,0.029]
Age ≥ 59 years		-0.296***	–0.275***	–0.195***
		[-0.332,-0.260]	[–0.327,-0.222]	[–0.253,-0.137]
Female × Age ≥ 59 years			–0.044	–0.040
			[–0.112,0.024]	[–0.101,0.020]
R-Squared	0.001	0.110	0.112	0.167
Older females (ref. older males)			–0.062**	–0.051**
			[–0.118,–0.007]	[–0.102,-0.000]
Older females (ref. younger females)			–0.319***	–0.236***
			[–0.365,–0.272]	[–0.284,–0.187]
Other controls	No	No	No	Yes
No. of observations	5980	5980	5980	5980

Note: Panel A displays exponentiated logit coefficients. Other controls: ethnic minority (=1 if Black, Asian or other ethnic minority, = 0 if White British), education (measured in 2017–19), marital status, household size, employment status, household income, health status, COVID-19 symptoms, risky behaviours (smoking and drinking), physical exercise, geographical location, pre-pandemic GHQ-12 score (measured in 2017-2019), GHQ-12 score in July 2020 and personality traits (measured in 2011–13). Survey design and sample weights are accounted for. 95% confidence intervals in brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

dysfunction in panel C) and internet use frequency across five different specifications, from Column 1 (without any control variable) to Column 5 (with a full set of control variables). While we do not find that internet use frequency is a statistically significant predictor of either the GHQ-12 score or the psychological distress score, high internet frequency use is negatively associated with the social dysfunction score. In other words, high internet frequency use appears to be a protective factor for social dysfunction. Those who use the internet more than twice a day score 0.085 standard deviations below in the social dysfunction score compared with those who use the internet twice a day or less. Table S5 in the Supplementary Material displays the estimates for all the control variables in Column (4).

We also re-ran the regressions in Table 5 using a comparable definition of internet use frequency for the same individuals, before (2017–19) and during the pandemic (September 2020), in Tables S6 and S7 in the Supplementary Material. If we compare the estimates from Table S6 with those from Table S7 (i.e. comparing estimates based on the same definition of the outcome variable but different time periods), we can conclude the findings differ between the pre-pandemic and the pandemic periods. If we compare the estimates from Table S7 with those from Table 5 (i.e. comparing estimates based on different definitions of the outcome variable but the same time period), we can conclude the findings are qualitatively very similar but less precisely estimated when using the everyday internet use definition. While the analysis using the pre-pandemic survey data is not directly comparable to our main analysis, we have discussed it here for the sake of completeness.

Finally, we have also investigated the possibility of a non-monotonic relationship between internet use frequency and mental health. [We use three internet use frequency categories: low (reference category: =1 if twice a day or less, =0 else), moderate (=1 if several times a day, =0 else) and high (=1 if almost all of the time, =0 else).] While the estimates are quite imprecise (Table S8 in the Supplementary Material), when looking at the relationship between mental health and social dysfunction, the point estimates of the coefficients on moderate and high are very similar. Thus, we do not find evidence of a non-monotonic relationship.

In Table 6, we focus on the relationship between mental health metrics (GHQ-12 in panel A, psychological distress in panel B, social dysfunction in panel C) and internet use purposes. Neither functional purpose nor leisure-and-learning purpose predicts any of our mental health metrics, at least when other control variables are accounted for. However, the use of internet for social purposes predicts mental health as measured by the social dysfunction score, regardless of the specification being used, without controls (Column 1, R-squared=0.016) or with a full set of control variables (Column 5, R-squared=0.262). In particular, in Column 5, we can see that a one standard deviation increase in the social purpose score is associated with a decrease in the social dysfunction score of 0.05 standard deviations. Table S9 in the Supplementary Material displays the estimates for all the control variables in Column (4).

These findings contrast with Braghieri *et al.* (2021), who use a natural experiment, namely the staggered introduction of Facebook across US colleges, and find evidence that social media use has a negative causal effect on mental health among college students in the USA. These divergent findings can be driven by several factors, including differences in the populations under study (i.e. college students in the USA vs. adults in the UK), differences in the empirical formulation and methodology of the analysis (e.g. indicator of Facebook availability at colleges in expansion group vs. social purpose score derived from PCA), and, perhaps more importantly, differences in the time period (our focus is on the COVID-19 pandemic period).

Finally, when interpreting the findings in Tables 5 and 6, it is important to take into account that different demographic groups use the internet at different frequencies and for different

Table 4. Do age and gender predict internet use purpose? (OLS)

	(1) Coef.	(2) Coef.	(3) Coef.	(4) Coef.
Panel A. Dependent variable: functional purpose score				
Female	–0.043		0.066	0.121**
	[–0.167,0.080]		[–0.041,0.174]	[0.010,0.231]
Age ≥ 59 years		–0.908***	–0.718***	-0.415***
		[–1.028,–0.788]	[–0.889,–0.546]	[-0.578,-0.252]
Female × age ≥ 59 years			–0.368***	–0.354***
			[–0.608,–0.127]	[–0.559,–0.149]
R-squared	0.000	0.152	0.159	0.252
Older females (ref. older males)			–0.301***	–0.233**
			[–0.516,–0.087]	[–0.419,–0.047]
Older females (ref. younger females)			–1.085***	–0.769***
			[–1.252,–0.919]	[–0.907,–0.630]
Panel B. Dependent variable: leisure-and-learning purpose score				
Female	–0.348***		–0.480***	–0.444***
	[–0.444,–0.252]		[–0.601,–0.358]	[–0.559,–0.328]
Age ≥ 59 years		–1.051***	–1.168***	–0.916***
		[–1.133,–0.970]	[–1.290,–1.046]	[–1.062,–0.771]
Female × age ≥ 59 years			0.180**	0.176**
			[0.030,0.329]	[0.038,0.313]
R-squared	0.025	0.226	0.262	0.337
Older females (ref. older males)			–0.300***	–0.268***
			[–0.389,–0.211]	[–0.353,–0.183]
Older females (ref. younger females)			–0.988***	–0.741***
			[–1.081,–0.895]	[–0.860,–0.622]
Panel C. Dependent variable: social purpose score				
Female	0.189***		0.141***	0.124**
	[0.103,0.274]		[0.045,0.237]	[0.026,0.221]
Age ≥ 59 years		–0.714***	–0.720***	–0.549***
		[–0.791,–0.636]	[–0.833,–0.607]	[–0.681,–0.417]
Female × age ≥ 59 years			0.027	0.017
			[–0.130,0.183]	[–0.131,0.165]
R-squared	0.009	0.121	0.126	0.164
Older females (ref. older males)			0.168***	0.141**
			[0.047,0.288]	[0.022,0.259]
Older females (ref. younger females)			–0.693***	–0.532***
			[–0.801,–0.585]	[–0.641,–0.423]
Other controls	No	No	No	Yes
No. of observations	5980	5980	5980	5980

Note: Other controls are described in the footer of Table 3. Survey design and sample weights are accounted for. 95% confidence intervals in brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

purposes and that frequency and purpose can have different effects across different groups. This heterogeneity can mask underlying group-specific relationships. For this reason, in the next subsection, we investigate whether the previous associations vary by gender and age.

Internet frequency use, internet use purpose and mental health by age and gender

We now investigate whether the relationships between internet use frequency, internet use purpose and mental health metrics vary by gender and age. This analysis is motivated by two sources of heterogeneity. First, as we have seen before, gender and age are important predictors of both internet use frequency and purpose. Second, it is well known that the COVID-19 pandemic has had a more detrimental effect on mental well-being among women and younger individuals than men and older individuals (Banks & Xu, 2020).

Figure 5 plots the coefficients on high internet use (more than twice a day) for men and women by age group (≥ 59 vs. < 59 years) after running separate regressions of mental health metrics by gender and age group. The figure reveals strong heterogeneities: internet use is a protective factor for mental health and social dysfunction among younger women but a risk factor for mental health and psychological distress among younger men. More specifically, we find that, among younger women, those who use the internet more than twice a day score (on average) 0.87 units below in the GHQ-12 compared with those who use the internet twice a day or less. Moreover, they score 0.29 standard deviations below in the social dysfunction score. Among younger men, we find that high use of internet is associated with increases in the GHQ-12 score of 0.73 units and in the psychological distress score of 0.16 standard deviations.

Figure 6 plots the coefficients on the different internet use purpose indicators (functional, leisure-and-learning, social) for men and women by age group after running separate regressions of mental health metrics by gender and age group. The figure reveals strong heterogeneities, too, while leisure-and-learning purpose is a protective factor for mental health and social dysfunction among younger women, it is a risk factor for mental health and social dysfunction among younger men. More specifically, among younger women, a one standard deviation increase in the leisure-and-learning purpose score is associated with decreases in the

Table 5. Does internet use frequency predict mental health? (OLS)

	(1) Coef.	(2) Coef.	(3) Coef.	(4) Coef.	(5) Coef.
Panel A. Dependent variable: GHQ-12 score (0–36)					
Internet high use	0.413	–0.361	–0.319	–0.258	–0.190
	[–0.151,0.977]	[–0.948,0.227]	[–0.817,0.178]	[–0.603,0.087]	[–0.521,0.141]
R-squared	0.001	0.040	0.168	0.530	0.549
Panel B. Dependent variable: psychological distress score					
Internet high use	0.248***	–0.006	–0.002	0.016	0.021
	[0.149,0.346]	[–0.103,0.090]	[–0.080,0.076]	[–0.041,0.072]	[–0.033,0.074]
R-squared	0.011	0.105	0.233	0.573	0.598
Panel C. Dependent variable: social dysfunction score					
Internet high use	–0.204***	–0.098*	–0.091*	–0.095**	–0.085**
	[–0.297,-0.110]	[–0.198,0.001]	[–0.185,0.003]	[–0.172,-0.018]	[–0.163,–0.007]
R-squared	0.007	0.018	0.049	0.249	0.260
No. of observations	5980	5980	5980	5980	5980
Age and age-squared	No	Yes	Yes	Yes	Yes
Female	No	Yes	Yes	Yes	Yes
Other controls	No	No	Yes	Yes	Yes
Mental health at $t-1$	No	No	No	Yes	Yes
Mental health in 2017-2019	No	No	No	No	Yes

Note: Other controls: ethnic minority (=1 if Black, Asian or other ethnic minority, = 0 if White British), education (measured in 2017–19), marital status, household size, employment status, household income, health status, COVID-19 symptoms, risky behaviours (smoking and drinking), physical exercise, geographical location and personality traits (measured in 2011–13). Mental health at $t-1$ is the corresponding lagged dependent variable (July 2020). Mental health in 2017–19 is the corresponding lagged dependent variable. 95% confidence intervals in brackets. Survey design and sample weights are accounted for. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 6. Does internet use purpose predict mental health? (OLS)

	(1) Coef.	(2) Coef.	(3) Coef.	(4) Coef.	(5) Coef.
Panel A. Dependent variable: GHQ-12 score (0–36)					
Functional purpose	–0.142	–0.300**	–0.106	–0.058	–0.025
	[–0.407,0.122]	[–0.573,–0.028]	[–0.344,0.131]	[0.211,0.094]	[0.173,0.124]
Leisure and	0.470***	0.361**	0.154	0.100	0.076
learning purpose	[0.144,0.796]	[0.041,0.681]	[–0.139,0.446]	[–0.105,0.305]	[–0.125,0.278]
Social purpose	0.255**	–0.014	–0.043	–0.165**	–0.193**
	[0.032,0.478]	[–0.248,0.220]	[–0.266,0.181]	[–0.326,–0.004]	[–0.349,–0.038]
R-squared	0.010	0.043	0.168	0.531	0.550
Panel B. Dependent variable: psychological distress score					
Functional purpose	0.020	–0.026	0.005	0.004	0.009
	[–0.029,0.070]	[–0.074,0.023]	[–0.035,0.044]	[–0.023,0.031]	[–0.017,0.035]
Leisure and	0.117***	0.054**	0.018	0.019	0.010
learning purpose	[0.062,0.173]	[0.001,0.108]	[–0.031,0.067]	[–0.015,0.053]	[–0.023,0.043]
Social purpose	0.108***	0.040*	0.037*	0.003	–0.003
	[0.067,0.150]	[–0.001,0.081]	[–0.001,0.076]	[–0.024,0.030]	[–0.029,0.023]
R-squared	0.042	0.109	0.235	0.574	0.598
Panel C. Dependent variable: social dysfunction score					
Functional purpose	–0.070***	–0.056**	–0.040	–0.028	–0.024
	[–0.117,–0.023]	[–0.107,–0.005]	[–0.089,0.009]	[–0.067,0.012]	[–0.064,0.016]
Leisure and	–0.016	0.033	0.021	0.007	0.009
learning purpose	[–0.072,0.041]	[–0.027,0.094]	[–0.032,0.074]	[–0.040,0.054]	[–0.038,0.056]
Social purpose	–0.066***	–0.054**	–0.059***	–0.054***	–0.054***
	[–0.106,–0.026]	[–0.097,–0.011]	[–0.104,–0.014]	[–0.093,–0.014]	[–0.094,–0.014]
R-squared	0.016	0.023	0.052	0.251	0.262
No. of observations	5980	5980	5980	5980	5980
Age and age-squared	No	Yes	Yes	Yes	Yes
Female	No	Yes	Yes	Yes	Yes
Other controls	No	No	Yes	Yes	Yes
Mental health at $t-1$	No	No	No	Yes	Yes
Mental health in 2017–19	No	No	No	No	Yes

Note: Other controls: ethnic minority (=1 if Black, Asian or other ethnic minority, = 0 if White British), education (measured in 2017-2019), marital status, household size, employment status, household income, health status, COVID-19 symptoms, risky behaviours (smoking and drinking), physical exercise, geographical location and personality traits (measured in 2011–13). Mental health at $t-1$ is the corresponding lagged dependent variable (July 2020). Mental health in 2017–19 is the corresponding lagged dependent variable. 95% confidence intervals in brackets. Survey design and sample weights are accounted for. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

GHQ-12 score of 0.31 units and in the social dysfunction score of 0.08 standard deviations. Among younger men, a one standard deviation increase in the leisure-and-learning purpose score is associated with increases in the GHQ-12 score of 0.50 units and in the social dysfunction score of 0.13 standard deviations.

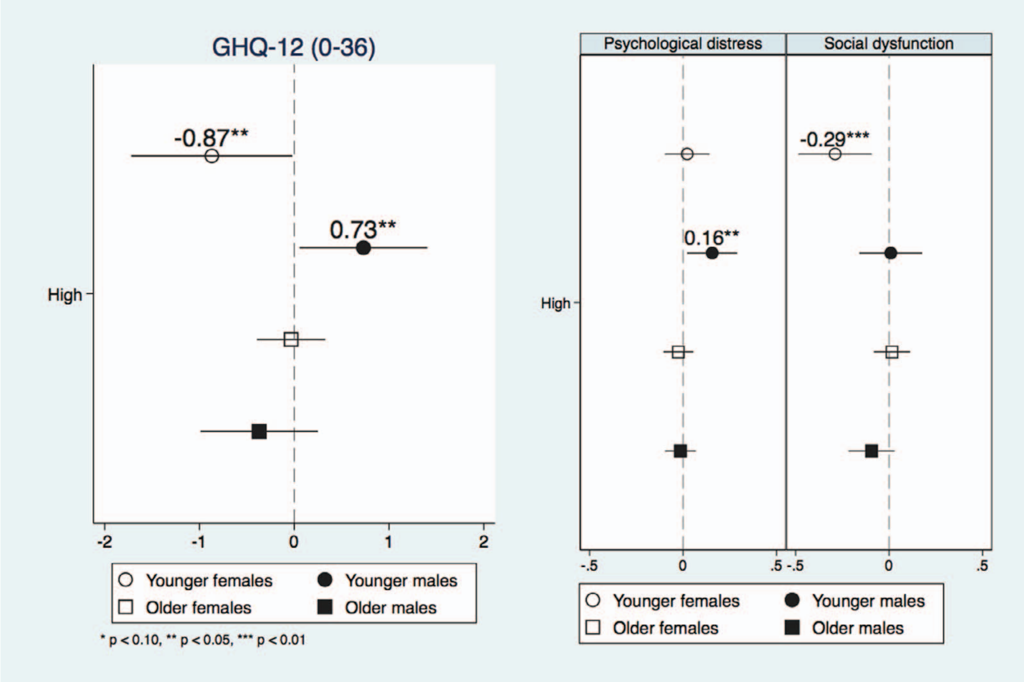

Figure 5. Does internet use frequency predict mental health differently by age and gender?

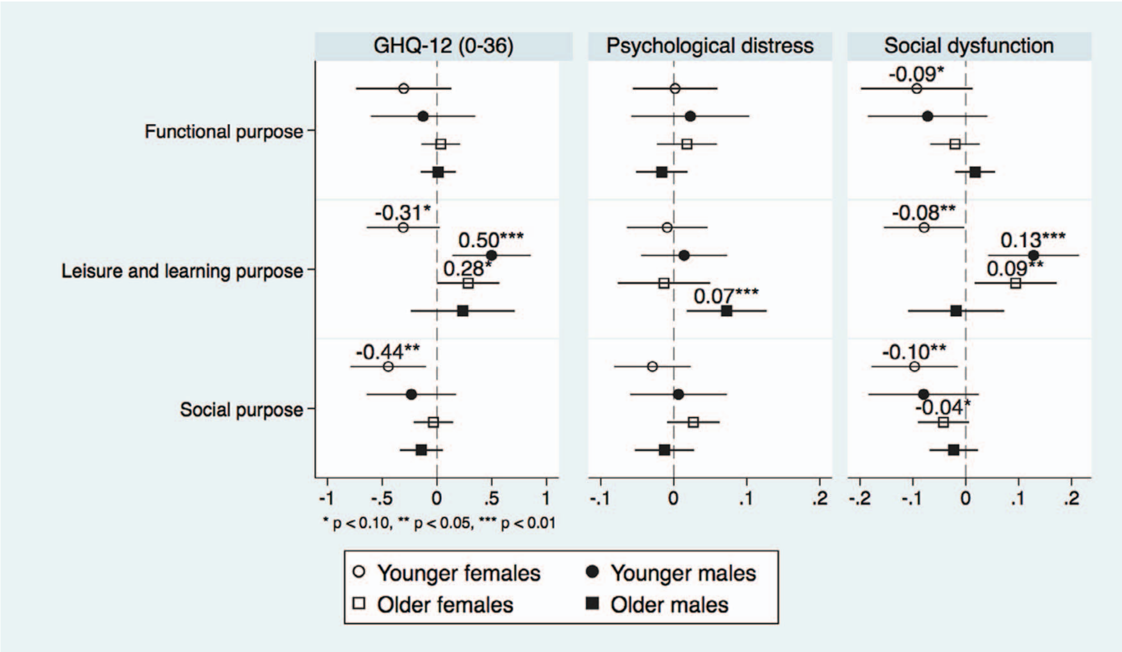

Figure 6. Does internet use purpose predict mental health differently by age and gender?

Statistical inference and causal interpretation

The purpose of this section is twofold. First, we want to assess whether our findings are statistically significant after accounting for multiple hypothesis testing. Second, while our analysis is essentially descriptive, we want to investigate whether a causal interpretation is plausible, in the sense that unobservable factors should be much more important than observables to argue that the documented association between the internet use frequency and mental health is entirely driven by the correlation between internet use frequency and unobservable factors.

First, we compare the p-values of individual hypothesis tests against those arising from multiple hypothesis tests. We present adjusted p-values using the step-down procedure of Romano & Wolf (2005, 2016) which controls for the family-wise error rate. For each sample (total and group sub-samples), we use the `rwolf2` command in Stata to calculate the adjusted p-values (Clarke, 2021, Clarke *et al.*, 2020) for the coefficients on internet use frequency and purposes.

Second, and in a similar spirit to Bryan *et al.* (2022), who investigate the impact of mental health on the probability of being in employment for prime age workers in the UK, we implement

Table 7. Sensitivity tests: internet use frequency

	Younger		Older	
	(1) female	(2) male	(3) female	(4) male
Panel A. Dependent variable: GHQ-12 score (0–36)				
Internet high use	–0.870	0.730	–0.039	–0.379
P-value	0.045	0.036	0.862	0.247
Adjusted p-value	0.082	0.099	0.983	0.707
δ	**9.62**	**2.83**		
Panel B. Dependent variable: psychological distress score				
Internet high use	0.022	0.156	–0.025	–0.014
P-value	0.719	0.023	0.561	0.747
Adjusted p-value	0.949	0.068	0.927	0.959
δ		**3.98**		
Panel C. Dependent variable: social dysfunction score				
Internet high use	–0.289	0.009	0.016	–0.094
P-value	0.004	0.916	0.753	0.137
Adjusted p-value	0.006	0.969	0.983	0.491
δ	**5.00**			
No. of observations	1756	1072	1693	1459

the bounds approach proposed by Oster (2019). This allows us to assess the plausibility of our estimates capturing a causal effect of internet use frequency on mental health. The key idea is to quantify how important unobservable factors should be relative to observable ones in order to nullify the significant estimated coefficients of internet use frequency. The relative importance is denoted by δ, and Oster (2019) suggests a threshold of 1. Specifically, $\delta = 1$ indicates that the unobservable factors need to be equally important as the observable factors so that the significant estimated coefficients can be nullified. Generally speaking, the higher the value of δ, the more plausible a causal interpretation is: the higher the value of δ, the more important unobservable factors should be relative to observable ones to attribute the documented relationship—between internet use frequency and mental health—to the correlation between internet use frequency and unobservable factors. We follow the suggestion by Oster (2019) to use 1.3 times the R-squared value of the most extensive specification.

The results of internet use frequency on mental health, presented in Table 7, are reassuring: our previous statistically significant findings are robust to adjusting for multiple testing (adjusted p-value < 0.1). Moreover, the smallest estimated δ is 2.83. This implies that selection on unobservable factors would have to be 283% as strong as selection on observable factors, for the estimated association between internet use frequency and mental health to be entirely driven by the relationship between internet use frequency and unobservable factors. Hence, our results appear to be robust to the omission of unobservable factors.

Finally, in Table 8, we adjust for multiple testing our p-values for the hypotheses about the relationship between internet purpose and mental health. Once again, most of our statistically significant findings are robust to adjusting for multiple testing (adjusted p-value < 0.1), except for the negative association between leisure and learning purpose score and the GHQ-12 score among younger women and the negative association between social purpose score and the social dysfunction score among older women. They were significant at the 10% level and become insignificant after adjusting for multiple testing.

The role of loneliness

We have seen that our previous findings are robust to multiple testing. What can explain the heterogeneous patterns across age and gender? While there could be many potential dimensions to be explored, including caring duties, contact with friends and family, neighbourhood cohesion and loneliness, only information on loneliness is available for the September 2020 wave. In this section, we analyse the role of loneliness in three different ways.

First, we assessed whether internet use frequency predicted loneliness, measured as how often the individual felt lonely in the last 4 weeks (https://www.understandingsociety.ac.uk/documentation/covid-19/dataset-documentation/variable/sclonely_cv). The findings from this analysis (Table S10 in the Supplementary Material) reveal that internet use frequency does *not* predict loneliness, regardless of the measure of loneliness being used: loneliness score (from 1=Hardly ever or never to 3=Often) or loneliness binary indicator (=1 if Some of the time or Often, =0 if Hardly ever or never).

Second, we also investigated whether the standardized loneliness score interacted with internet use frequency in explaining mental health. To that end, we re-ran the analysis in Table 5 after adding both the standardized loneliness score and the interaction between the standardized loneliness and internet use frequency. This analysis (Table S11 in the Supplementary Material) reveals that loneliness is a predictor of all mental health scores (the GHQ-12 score, the psychological distress score and the social dysfunction score), but the relationship between internet use frequency and mental health does *not* depend on loneliness.

Finally, we re-ran the analysis by age group and gender. Interestingly, in Table 9, we find that among young women, the relationship between internet use frequency and the social dysfunction score is stronger among those who score higher in the loneliness indicator, so that those who use frequent internet and are lonely display a lower (better) social dysfunction score than those who do not frequently use internet and are lonely. For young men, Table 10, the interpretation of our findings is less clear-cut, but if anything, we find that frequent internet use is associated with worse mental health (higher GHQ-12 score) among those who feel lonelier. No interactions are found between loneliness

Table 8. Sensitivity tests: internet use purposes

	Younger		Older	
	(1) female	(2) male	(3) female	(4) male
Panel A. Dependent variable: GHQ-12 score (0–36)				
Functional purpose score	–0.304	–0.127	0.035	0.011
P-value	0.179	0.613	0.708	0.895
Adjusted p-value	0.327	0.965	0.983	0.959
Leisure-and-learning purpose	–0.308	0.498	0.285	0.235
P-value	0.069	0.008	0.049	0.337
Adjusted p-value	0.124	**0.021**	0.114	0.827
Social purpose score	–0.445	–0.234	–0.032	–0.143
P-value	0.010	0.273	0.733	0.172
Adjusted p-value	**0.015**	0.665	0.983	0.521
Panel B. Dependent variable: psychological distress score				
Functional purpose score	0.002	0.023	0.018	–0.016
P-value	0.952	0.592	0.399	0.375
Adjusted p-value	0.949	0.965	0.860	0.827
Leisure-and-learning purpose score	–0.009	0.014	–0.013	0.072
P-value	0.751	0.656	0.667	0.013
Adjusted p-value	0.949	0.965	0.983	**0.031**
Social purpose score	–0.029	0.006	0.027	–0.013
P-value	0.279	0.853	0.170	0.546
Adjusted p-value	0.481	0.969	0.393	0.900
Panel C. Dependent variable: social dysfunction score				
Functional purpose score	–0.093	–0.072	–0.020	0.018
P-value	0.089	0.214	0.405	0.370
Adjusted p-value	0.146	0.585	0.860	0.827
Leisure-and-learning purpose score	–0.079	0.128	0.094	–0.018
P-value	0.052	0.004	0.019	0.704
Adjusted p-value	**0.082**	**0.013**	**0.030**	0.959
Social purpose score	–0.097	–0.080	–0.042	–0.023
P-value	0.018	0.139	0.087	0.339
Adjusted p-value	**0.036**	0.416	0.229	0.827
No. of observations	1756	1072	1693	1459

and internet use frequency among older individuals, regardless of their gender (Tables S12 and S13 in the Supplementary Material).

The patterns in Tables 9 and 10 are consistent with the heterogeneity reported in Fig. 5. They highlight that the relationship between internet use and loneliness is a complex one: internet use may increase loneliness by replacing offline relationships, but it may reduce loneliness by enhancing existing relationships (Nowland *et al.*, 2018). While our results are suggestive of potential interactions between loneliness and internet use, we see them as purely exploratory, descriptive findings, which may foster new hypotheses for future research.

Discussion

Our analysis suggests that only younger women are benefiting from using the internet more often during the pandemic, while it is a risk factor for other groups. This finding somewhat contrasts with the finding in Golin (2022) that broadband Internet leads to worse mental health for women, but not for men, in Germany—her finding is driven by women aged 17–30 years. As highlighted previously, there are several differences between Golin's study and ours, including the fact that the period analysed by Golin (2022) does not cover the COVID-19 pandemic.

As for older groups, our findings also differ from previous studies. During the COVID-19 pandemic, Nimrod (2020) use a random sample of 407 Israeli internet users aged 60 years and over and find that increased internet use for leisure (games, downloading content, websites related to hobbies, writing entries in blogs, forums, etc.) is significantly associated with enhanced wellbeing in April 2020, during the lockdown. However, we find that leisure-and-learning internet use purpose is a risk factor among older respondents.

The discrepancy in these findings can be driven by multiple reasons, chief among them is the fact that these are different samples and the fact that one survey refers to April 2020 (during lockdown in Israel) while the other to September 2020 (no lockdown in the UK). Indeed, there is longitudinal evidence from Italy (between 12 March 2020 and 7 June 2020) that the online social connections can be a protective factor from psychological distress under highly restrictive isolation (strong lockdown) conditions but not under mild isolation conditions (Marinucci *et al.*, 2022). Recent work by Altindag *et al.* (2021) provides causal evidence on the negative impact of lockdowns on mental health exploiting a natural experiment in Turkey (those born in December 1955 and before were under curfew, those born in January 1956 or after were exempt).

We do not find a significant relationship between social purpose and mental health among older individuals. (Lam *et al.* (2020) use the English Longitudinal Study of Ageing to study the relationship between internet use and purpose and mental wellbeing in the English population aged 50 years and older. They found that infrequent internet use (monthly or less vs. daily) was negatively related with life satisfaction. Moreover, while using the

Table 9. Does loneliness interact with internet use frequency in explaining mental health of younger females? (OLS)

	GHQ-12 score (0-36)	Psychological distress score	Social dysfunction score
Panel A. Without controls			
Internet high use	–0.828*	0.094	–0.363***
	[–1.794,0.139]	[–0.056,0.244]	[–0.552,–0.174]
Lonliness (standardized)	4.100***	0.478***	0.565***
	[2.431,5.769]	[0.294,0.661]	[0.261,0.869]
High × loneliness	–0.877	0.036	–0.294*
	[–2.593,0.839]	[–0.158,0.229]	[–0.613,0.024]
R-Squared	0.313	0.266	0.100
Panel B. Age			
Internet high use	–0.740	0.045	–0.275***
	[–1.711,0.231]	[–0.109,0.200]	[–0.476,–0.075]
Lonliness (standardized)	4.106***	0.475***	0.569***
	[2.439,5.772]	[0.293,0.658]	[0.269,0.870]
High × loneliness	–0.865	0.026	–0.279*
	[–2.575,0.846]	[–0.167,0.219]	[–0.593,0.036]
R-Squared	0.313	0.270	0.108
Panel C. Age and other controls			
Internet high use	–0.723*	0.028	–0.249***
	[–1.560,0.113]	[–0.112,0.169]	[–0.437,–0.062]
Lonliness (standardized)	3.642***	0.427***	0.497***
	[2.360,4.924]	[0.277,0.578]	[0.247,0.747]
High × loneliness	–0.760	0.023	–0.246*
	[–2.078,0.557]	[–0.138,0.184]	[–0.508,0.016]
R-Squared	0.381	0.330	0.148
Panel D. Age, other controls and mental health at $t-1$			
Internet high use	–0.729**	0.017	–0.240***
	[–1.436,–0.021]	[–0.096,0.131]	[–0.404,–0.076]
Lonliness (standardized)	2.218***	0.198***	0.362***
	[1.334,3.102]	[0.083,0.314]	[0.185,0.538]
High × loneliness	–0.656	0.048	–0.244**
	[–1.527,0.214]	[–0.071,0.167]	[–0.431,–0.058]
R-squared	0.550	0.547	0.291
Panel E. Age, other controls, mental health ($t-1$ **and 2017–19)**			
Internet high use	–0.571	0.041	–0.221***
	[–1.276,0.134]	[–0.074,0.156]	[–0.386,–0.057]
Lonliness (standardized)	2.157***	0.186***	0.360***
	[1.287,3.028]	[0.074,0.299]	[0.175,0.544]
High × loneliness	–0.677	0.048	–0.250**
	[–1.535,0.181]	[–0.068,0.164]	[–0.444,–0.056]
R-squared	0.566	0.567	0.304
No. of observations	1756	1756	1756

Note: Other controls are described in the footer of Table 5. 95% confidence intervals in brackets. Survey design and sample weights are accounted for. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

internet for communication purposes was positively related with life satisfaction, internet use for information access was negatively related with life satisfaction.] This is consistent with face-to-face communication not being able to be replaced by online communication (Marinucci et al., 2022). Elderly people usually interact in daycare venues, community centres and places of worship (Armitage & Nellums, 2020). Although increased internet use for leisure may enhance a sense of social engagement, reduce loneliness and compensate for the reduced leisure repertoire during the lockdown, it might increase the time being online alone when the elderly could actually spend time outdoors (in the absence of a lockdown). While online technologies could be harnessed to provide social support networks and a sense of belonging (Newman & Zainal, 2020), they cannot replace offline activities.

As for younger groups, our findings show strong gender differences in internet use patterns, and the relationship between internet use and mental health. Consistent with previous research, we find that males are more likely to watch videos and listen to music, whereas females are more inclined to use communication functions and social networking services (Chen et al., 2017, Lemenager et al., 2021).

The gender differences documented in this study resonate with recent research highlighting that women are more likely to focus on COVID-19 issues related to family, social distancing and healthcare, while men are more likely to focus on COVID-19 issues related to sports cancellations, the global spread of the pandemic and political reactions (Thelwall & Thelwall, 2020).

Internet use is a protective factor for mental health in women, especially in the social dysfunction dimension, perhaps by allowing them to be in touch with their close friends, family and social networks. Women may be more likely to share what video they watched or what music they listened to or conduct online leisure activities together with others. It has been found that

Table 10. Does loneliness interact with internet use frequency in explaining mental health of younger males? (OLS)

	GHQ-12 score (0-36)	Psychological distress score	Social dysfunction score
Panel A. Without controls			
Internet high use	1.215**	0.224*	0.053
	[0.224,2.205]	[-0.019,0.467]	[-0.130,0.236]
Lonliness (standardized)	1.749***	0.305**	0.106
	[0.469,3.029]	[0.050,0.560]	[-0.062,0.273]
High × loneliness	1.535**	0.197	0.190*
	[0.010,3.061]	[-0.092,0.486]	[-0.029,0.409]
R-Squared	0.339	0.263	0.080
Panel B. Age			
Internet high use	1.392***	0.218*	0.113
	[0.452,2.331]	[-0.034,0.469]	[-0.067,0.293]
Lonliness (standardized)	1.784***	0.302**	0.121
	[0.533,3.036]	[0.043,0.561]	[-0.055,0.298]
High × loneliness	1.547**	0.195	0.196*
	[0.046,3.047]	[-0.097,0.487]	[-0.029,0.422]
R-Squared	0.342	0.265	0.093
Panel C. Age and other controls			
Internet high use	1.141**	0.207**	0.057
	[0.254,2.029]	[0.008,0.407]	[-0.112,0.227]
Lonliness (standardized)	1.645***	0.229**	0.173**
	[0.511,2.778]	[0.023,0.436]	[0.020,0.326]
High × loneliness	1.416**	0.215*	0.135
	[0.141,2.691]	[-0.006,0.437]	[-0.069,0.340]
R-Squared	0.397	0.348	0.146
Panel D. Age, other controls and mental health at $t-1$			
Internet high use	0.786**	0.177**	0.002
	[0.115,1.456]	[0.019,0.336]	[-0.161,0.164]
Lonliness (standardized)	1.002**	0.083	0.161***
	[0.221,1.783]	[-0.098,0.265]	[0.040,0.282]
High × loneliness	0.695	0.144	0.033
	[-0.195,1.585]	[-0.047,0.335]	[-0.137,0.203]
R-Squared	0.557	0.574	0.262
Panel E. Age, other controls, mental health ($t-1$ **and 2017-2019)**			
Internet high use	0.786**	0.158**	0.007
	[0.120,1.452]	[0.020,0.296]	[-0.156,0.170]
Lonliness (standardized)	0.905**	0.080	0.149**
	[0.165,1.645]	[-0.078,0.239]	[0.028,0.270]
High × loneliness	0.734*	0.132	0.041
	[-0.120,1.588]	[-0.036,0.300]	[-0.127,0.209]
R-Squared	0.564	0.602	0.264
No. of Observations	1072	1072	1072

Note: Other controls are described in the footer of Table 5. 95% confidence intervals in brackets. Survey design and sample weights are accounted for. * p<0.10, ** p<0.05, *** p<0.01

greater use of socially supportive coping strategies was associated with a faster rate of improvements in mental health during the pandemic (Fluharty *et al.*, 2021). Combined with our findings, using the internet more for social activities can be a protective factor for mental health, particularly marked among women. Among younger men, reducing online activity and increasing offline socializing with family and friends may be associated with better mental health.

Conclusion

This paper has documented several robust findings about the relationship between internet and mental health during the COVID-19 pandemic in the UK. Generally, high-frequency internet use appears to be a protective factor for social dysfunction and the use of internet for social purposes appears to be a protective factor for social dysfunction. However, we find heterogeneous relationships across age and gender groups.

First, no significant relationship is found between high frequency internet use (more than twice a day) and mental health among older respondents (aged 59 years and above). Second, among younger respondents, high frequency internet use is a protective factor for social dysfunction in women but a risk factor for psychological distress in men. Third, among older respondents, we find that using the Internet for leisure-and-learning purposes more often is a risk factor for psychological distress in men and a risk factor for social dysfunction in women. Fourth, while leisure-and-learning purpose is a protective factor for social dysfunction among younger women, it is a risk factor for social dysfunction among younger men. Finally, social purpose is a protective factor for social dysfunction among younger women.

We also show that there is a role for loneliness in explaining the heterogeneous relationship between internet use and mental health by age and gender. We find that internet may be a protective factor for young women's mental health (social dysfunction score) among those who feel lonelier, and—if anything—a risk factor for young men's mental health (GHQ-12 score), particularly among those who feel lonelier. While purely exploratory and descriptive, these findings highlight the complexity of the relationship between internet use and loneliness (Nowland *et al.*, 2018).

The main advantages of our study with respect to other studies on the relationship between internet and mental health during the COVID-19 pandemic are twofold: first, the use of a large representative sample; second, the rich internet data on both use frequency and purposes, after contributing suggested content that became the internet use module of the September 2020 COVID-19 wave study.

While our findings may suggest the importance of considering gender-targeted prevention and intervention strategies to instruct internet use and promote mental health, our study has four key limitations that must be acknowledged. First, we use observational data in a cross-sectional setting, which limits the ability to draw causal statements. Second, the data on internet use and mental health status refer to a particular point in time during the COVID-19 pandemic, September 2020, which limits the generalization of the our findings to other time periods (Quintana-Domeque & Proto, 2022). Third, while the GHQ-12 has been extensively validated and used in several COVID-19 related studies, it has some well-known limitations, including low predictive value (Hankins, 2008b). Finally, self-reported internet and, more generally, digital media use are expected to suffer from measurement error (Araujo *et al.*, 2017, Parry, 2021, Scharkow, 2016). Hence, future research should focus not only on identification issues but also on measurement error concerns.

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Conflict of interest statement

None declared.

Data and code availability

The research data are distributed by the UK Data Service. Researchers who would like to use Understanding Society need to register with the UK Data Service before being allowed to apply for or download datasets. For more information, visit the link. The code to replicate the analysis in this paper is publicly available from the Harvard Dataverse repository: https://doi.org/10.7910/DVN/VD0TSO.

Disclaimer

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Appendix

A Principal Components Analysis

Principal component analysis (PCA) is a variable reduction technique that reduces the number of variables while retaining most of the variance of the variables Abdi & Williams (2010), Wold *et al.* (1987). We use PCA to extract the most important information from online activities. After applying PCA, variables called principal components (PC) are generated. The first PC contains most of the information of the observed variables and the second PC contains most of the information of the residual variance, and so on. To simplify the interpretation of the PC, we use Promax rotation to minimize the high loadings in each component. Promax rotation also allows PCs to be correlated. Table A1 provides the loadings in each component after Promax rotation.

Table A1. PCA: rotated component matrix for online activities

	Factor Loadings		
Activities	**Component1**	**Component2**	**Component3**
Browsing websites	**0.486**	-0.030	0.115
Email	**0.546**	-0.042	-0.005
Looking at Social Media	0.132	-0.043	**0.595**
Posting on Social Media	-0.000	-0.050	**0.673**
Online banking	**0.436**	0.064	-0.013
Online buying	**0.463**	0.068	0.001
Gaming	-0.187	0.222	**0.416**
Streaming videos	-0.031	**0.615**	-0.001
Streaming music	0.003	**0.592**	-0.012
Education	0.099	**0.454**	-0.096

B Exploratory Factor Analysis

We use the exploratory factor analysis (EFA) (see Williams *et al.*, 2010, for more details). EFA is different from PCA. EFA hypothesizes an underlying factor structure of a set of variables and identifies the latent constructs. Before EFA, we follow the literature testing the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity to assess the suitability of our data for factor analysis. The KMO index ranges from 0 to 1. An index greater than 0.5 indicates adequate sample size for the factor analysis. The null hypothesis for Bartlett test is that variables are not inter-correlated. The KMO index of our data was 0.939. Bartlett's test of sphericity was significant (χ^2 = 87149.33, df = 66, p = 0.000).

We then use EFA and the Varimax rotation method. Varimax rotation produces factor structures that are uncorrelated and simplifies the interpretation of the factors by minimizing the number of variables that have high loadings on each factor Williams *et al.* (2010). We use Kaiser's rule to determine the number of factors in the solution Kaiser (1960). The Kaiser's criteria consists in using factors with eigenvalues greater than 1. The eigenvalue is a measure of the variance of the original variables that a factor explains. If an eigenvalue is less than 1, it means that the factor explains less than a single original variable, that is, the original variable is better than the generated factor.

The EFA yielded a two-factor solution, explaining 73.73% of the total variance in items (factor 1 eigenvalue = 7.67 and factor 2 eigenvalue = 1.17). We label the factors psychological distress and social dysfunction. Items 2, 5, 6, 9, 10 and 11 correspond to psychological distress and the rest items correspond to social dysfunction (see factor loadings in Table B1). The EFA result is consistent with previous literature Hankins (2008a), Montazeri *et al.* (2003), Werneke *et al.* (2000).

Table B1. Explanatory factor analysis: rotated component matrix for the GHQ-12

	Factor Loadings	
Item	**Factor1**	**Factor2**
GHQ: concentration	0.380	**0.727**
GHQ: loss of sleep	**0.765**	0.234
GHQ: playing a useful role	0.261	**0.787**
GHQ: capable of making decisions	0.322	**0.819**
GHQ: constantly under strain	**0.823**	0.252
GHQ: problem overcoming difficulties	**0.831**	0.346
GHQ: enjoy day-to-day activities	0.279	**0.752**
GHQ: ability to face problems	0.475	**0.747**
GHQ: unhappy or depressed	**0.809**	0.413
GHQ: losing confidence	**0.815**	0.385
GHQ: believe worthless	**0.777**	0.356
GHQ: general happiness	0.459	**0.719**

However, we need to interpret the two-factor result as the two-dimension of the GHQ-12 cautiously. Some studies suggest that the GHQ-12 measures qualitatively different constructs Graetz (1991), Hu *et al.* (2007), Politi *et al.* (1994). Others suggest that the two factors identified may be resulting from positive and negative wording of the questions. In that case, the two-factor GHQ-12 is a methodological artefact which results from wording effects Gnambs & Staufenbiel (2018), Hankins (2008a). Unfortunately, the number of dimensions of the GHQ-12 is still subject to an ongoing debate. We use the two-factor results in this study, which also helps to take potential response bias for positively/negatively phrased items into account.

C List of variables and definitions

Table C1. Variable Definition

Mental Wellbeing and Internet Use	
GHQ-12 score (0-36)	Self-assessed mental wellbeing (0-36 scale, higher score = poorer mental wellbeing)
Psychological distress score (standardized)	one dimension of GHQ-12, derived from the factor analysis
Social dysfunction score (standardized)	another dimension of GHQ-12, derived from the factor analysis
Internet high use frequency	The frequency of personal internet use. 0 if in low level (once or twice a time a day or less), 1 if in high level (several times a day or almost all of the time)
Functional purpose (standardized)	One of the personal internet use purposes. A component derived from the PCA. Highly contributing variables are browsing websites, email, online banking and online buying.
Leisure-and-learning purpose (standardized)	One of the personal internet use purposes. A component derived from the PCA. Highly contributing variables are streaming videos, streaming music and online education.
Social purpose (standardized)	One of the personal internet use purposes. A component derived from the PCA. Highly contributing variables are looking at social media, posting on social media and gaming.
Demographics and Socio-economic Characteristics	
Age	Age of the respondent in years
Female	1 if female, 0 if male
Ethnic Minority	1 if Black, Asian or other ethnic minority, 0 if White British
Education	1 if higher education (university +) in 2017-2019, 0 otherwise
Employment status	1 if employed (if employed and/or self-employed), 0 otherwise
Marital status	1 if living with a partner, 0 otherwise
Household size	1 if number of individuals in household greater than two, 0 otherwise
Household income	Natural log of usual weekly total household gross income
Physical Health	
COVID-19 symptoms	1 if has/had symptoms that could be coronavirus, 0 otherwise
Health status	1 if has long term health condition, 0 otherwise
Smoking	1 if smoking cigarettes (not including e-cigarettes), 0 otherwise
Drinking	1 if drinking heavily on a ‘Weekly’ or ‘Daily or almost daily’ basis, 0 otherwise
Physical exercise	1 if did moderate exercise or vigorous exercise on three days in the previous week, 0 otherwise
Big Five Personality Traits in 2011-2013	
Agreeableness	Levels of agreeableness (1-7 scale, higher score = higher levels)
Conscientiousness	Levels of conscientiousness (1-7 scale, higher score = higher levels)
Extraversion	Levels of extraversion (1-7 scale, higher score = higher levels)
Neuroticism	Levels of neuroticism (1-7 scale, higher score = higher levels)
Openness	Levels of openness (1-7 scale, higher score = higher levels)
Geographical Variables	
Geographic location	12 macro geographic locations https://www.understandingsociety.ac.uk/documentation/mainstage/dataset-documentation/variable/gor_dv (12 binary indicators)

D Attrition

Table D1. Comparison of sample sizes and average key characteristics: September 2020 Sample vs. Final Matched Sample

	September 2020 Sample		Final Matched Sample			
	N	Mean	N	Mean	Mean Diff	Diff. P-value
GHQ-12 score (0-36)	10267	12.07	5980	11.85	-0.22	0.002
Internet high use frequency (0-1)	10347	0.75	5980	0.74	-0.01	0.198
Age	10607	50.25	5980	54.65	4.4	0.000
Female (0-1)	10598	0.53	5980	0.54	0.01	0.504
Ethnicity Minority (0-1)	10552	0.13	5980	0.08	-0.05	0.000
Higher education (0-1)	10535	0.42	5980	0.47	0.05	0.011
Living with partner (0-1)	10607	0.62	5980	0.69	0.07	0.031
Employed (0-1)	10560	0.59	5980	0.60	0.01	0.024
log Weekly Household Income	8604	5.49	5980	5.60	0.11	0.046
Has/ Had COVID-19 symptoms (0-1)	10600	0.16	5980	0.16	0	0.544
Smoker (0-1)	10336	0.11	5980	0.10	-0.01	0.022
Heavily Drinking (0-1)	10317	0.15	5980	0.16	0.01	0.088
Regular exercise (0-1)	9647	0.50	5980	0.50	0	0.847
Agreeableness (1-7)	8589	5.55	5980	5.55	0	0.752
Conscientiousness (1-7)	8590	5.47	5980	5.50	0.03	0.119
Extraversion (1-7)	8590	4.50	5980	4.50	0	0.698
Neuroticism (1-7)	8590	3.62	5980	3.58	-0.04	0.138
Openness (1-7)	8589	4.57	5980	4.59	0.02	0.371
Observations	10607		5980			

E Means and (standard deviations) of the variables used in the analysis

Table E1. Means and (standard deviations) of the variables used in the analysis

	Mean	(Std. Dev)
GHQ-12 score (0-36)	11.848	(5.564)
Psychological distress score (standardized)	0.106	(0.999)
Social dysfunction score (standardized)	-0.015	(1.022)
Internet high use frequency (0-1)	0.736	
Functional purpose score (standardized)	-0.084	(1.114)
Leisure-and-learning purpose score (standardized)	0.142	(1.056)
Social purpose score (standardized)	0.071	(0.982)
Age (years)	54.650	(14.655)
Female (0-1)	0.538	
Ethnic minority (0-1)	0.084	
Higher education (0-1)	0.472	
Employed (0-1)	0.600	
Living with partner (0-1)	0.691	
Household size >2 (0-1)	0.235	
log Weekly Household Income	5.596	(2.107)
Has/ Had COVID-19 symptoms (0-1)	0.156	
Has long term health condition (0-1)	0.554	
Smoking (0-1)	0.102	
Heavy drinking (0-1)	0.163	
Regular exercise (0-1)	0.499	
North East (0-1)	0.042	
North West (0-1)	0.103	
Yorkshire and The Humber (0-1)	0.079	
East Midlands (0-1)	0.082	
West Midlands (0-1)	0.080	
East of England (0-1)	0.112	
London (0-1)	0.094	
South East (0-1)	0.157	
South West (0-1)	0.098	
Wales (0-1)	0.041	
Scotland (0-1)	0.087	
Northern Ireland (0-1)	0.024	
Agreeableness (1-7)	5.551	(0.976)
Conscientiousness (1-7)	5.502	(1.000)
Extraversion (1-7)	4.498	(1.264)
Neuroticism (1-7)	3.576	(1.350)
Openness (1-7)	4.590	(1.171)
GHQ-12 score in 2017-2019	11.089	(5.347)
GHQ-12 score in July 2020	11.644	(5.518)
Observations	5980	

Note: Survey design and sample weights are accounted for.