Healthcare utilisation and physical activities for older adults with comorbidities in the UK during COVID-19

Abstract

A major concern with COVID-19 was the impact it would have on individual health, the routine use of healthcare services, and physical activities, especially for older adults with comorbidities. To address this, we studied the association between these variables for older adults during the pandemic. To explore what policy instruments might be effective in mitigating the negative impacts, we investigated the effects of a shielding notice for those identified as vulnerable by the government and social media given it has been an important source for disseminating information of COVID-19. We employed a UK sample with 3,807 participants aged ≥ 50 from an online survey administered during May and June 2020. Based on numbers of comorbidities, we separated the sample into a higher comorbidity group with those in the upper quartile of the sample (n=829) and a lower comorbidity group with the remainder (n=2,978). Statistical methods include Chi-squared analyses and cross-sectional regressions. We found that individuals with higher comorbidities were more likely to have poorer self-reported health and mental health and to receive a shielding notice from the government compared to those without ($p<0.05$). Decreases in physical activities were associated with poorer self-reported health and the increases were associated with better self-reported health; on the other hand, the decreases were associated with poorer mental health, but the increases did not link to better mental health. Examination of the effects of policy instruments show that a shielding notice was positively associated with primary care use. The notice generated greater reliance on telephone/video consultations compared to in-person consultations, but the impacts were less strong for people with higher comorbidities.

Frequent use of social media raised the probability of increasing physical activities and reduced that of decreasing physical activities, implying social media being an effective tool in promoting physical activities during lockdown and subsequent restrictions.

Key words: healthcare utilisation, physical activity, social media, COVID-19, comorbidity, older adults, shielding

What is already known about this topic?

- Risks of severe illness from COVID-19 increase with age and comorbidities.
- Health status of people with comorbidities deteriorated more than others during COVID-19.
- The COVID-19 pandemic affected the patterns of healthcare utilisation and physical activities.

What this paper adds?

- A shielding notice was positively related to healthcare utilisation, with greater impact on telephone/video consultations compared to in-person consultations.
- Familiarity with social media was associated with changes in physical activities but not healthcare utilisation.
- Self-reported health was positively associated with increases in physical activities and negatively with the decreases. Decreases in physical activities during the pandemic were associated with poorer mental health, but the increases did not link to better mental health.

1. Introduction

A major concern with COVID-19 was the impact it would have on the routine use of healthcare services, physical activities and individual health, especially for those older individuals with comorbidities (Wong et al., 2020). A key unknown is related to how familiarity with social media and/or a shielding notice from the government affect the associations between healthcare utilisation, physical activities, and health for older individuals with comorbidities.

The concurrence of multiple diseases intensifies individuals' reliance on healthcare (Gijsen et al., 2001). As risks of severe illness from COVID-19 increase with age and comorbidities, an exploration of healthcare utilisation of those with higher comorbidities is especially needed (Atkins et al., 2020). Adequate physical activities are helpful to maintain both physical and mental health during the pandemic, but changes in physical activities during lockdown and subsequent restrictions are unclear. It may be that individuals reduce their physical activities in order to obey the restrictions in use of gyms, leisure centres and tourist attractions. Conversely, individuals may raise their physical activities due to changes in working routine and/or because they become more aware of the need to maintain their own health during the pandemic.

The detrimental impact of social isolation on both physical and mental health has been confirmed in the literature (Courtin and Knapp, 2017). These detrimental impacts may be amplified in lockdown because of the restrictions regarding interpersonal interaction. The UK government advised people who are at higher risk of serious illness with the coronavirus to take additional actions to protect themselves. One suggestive action was to 'shield' so that

their interaction outside was kept to an absolute minimum (Public Health England, 2020). Individuals receiving this shielding notice may rely more on telephone/video consultations than in-person consultations due to the concern of interpersonal interaction. In addition to the advice from the government, social media also played an important role in disseminating key information of COVID-19 (Chan et al., 2020, El-Awaisi et al., 2020). Social media could therefore be another instrument to mitigate the negative impact of lockdown in that it raised the awareness and thus may influence individuals' behaviours.

It is clear that lockdown restrictions pose significant impact on life routine, but how it affected older adults with comorbidities and what policy makers can do to mitigate the negative impacts are still unclear. This paper aims to further the understanding of the impacts of lockdown and the effects of potential policy instruments including a shielding notice and social media.

2. Methods

In accordance with the Center for Open Science recommendations (Nosek et al., 2017), we report in this section an overview of the conditions under which the data were collected, any exclusion criteria, our sample sizes and the measures available and used.

2.1. Data

The sample that we used was taken from the Platform for Research Online to Investigate Genetics and Cognition in Aging (PROTECT: https://www.protectstudy.org.uk/) in the UK. The PROTECT study has been collecting health-related information of individuals aged 50 or over

since 2015 initially to understand how healthy brains age and why people develop dementia (Creese et al., 2019). Each year, participants in PROTECT are asked to complete an online survey. In response to the first lockdown in March 2020, PROTECT released a new survey to examine the impacts of COVID-19 during May and June 2020. Among the 23,851 participants, 3,843 completed the COVID-19 survey. Participants were excluded from the analysis if information on age and/or comorbidities were missing. The resulting sample in this paper consists of 3,807 participants after removing those without the information of age (n=14), comorbidities (n=27) or both (n=8). The University of Exeter's Information Governance and Security policies regulate access to the PROTECT data. The coding script for the analysis conducted in this paper is available from the authors on request.

2.2. Measures

Comorbidities

The PROTECT study collects self-reported information on: high blood pressure, stroke, heart disease, diabetes, mild cognitive impairment, Parkinson's disease, high cholesterol, hypothyroidism, hyperthyroidism, arthritis, Huntington's disease, cancer, osteoporosis, asthma, epilepsy, multiple sclerosis, motor neurone disease, Paget's disease and deep vein thrombosis. Based on the number of comorbidities, we categorised participants into a higher comorbidity group for those in the upper quartile of the sample (n=829) and a lower comorbidity group for the remainder (n=2,978).

Shielding notice

A shielding notice was captured by the question "whether you received a letter advising you to shield" (yes/no) in the survey.

Self-reported health and mental health

Individual health status was measured by self-reported health (poor/fair/good/excellent) in the survey. We measured mental health with the variables of feeling depressed (never/several days/more than half of the days/nearly every day) and feeling lonely (hardly ever/some of the time/often) respectively. These measures were chosen because they reflect the general health and mental health status during the lockdown period.

Changes in physical activities

Changes in physical activities during the pandemic period were taken from the question "how have your levels of physical activity changed since 23rd March 2020". Documented answers include increase, decrease and no change. Another question related to physical activities was "since 23rd March 2020, how often have you left your home to exercise". Although this question captures the frequency, it is restricted to outdoor exercise, and so excludes home workouts that increased in popularity during lockdown.

Healthcare utilisation

Measures for healthcare utilisation were taken from self-reported questions "In the last four weeks, how many telephone/video consultations have you had with a doctor/other health professional?" and "In the last four weeks, how many in person consultations have you had with a doctor/other health professional?" respectively.

Our data has two other measures for individual's healthcare utilisation: the numbers of calls made to 999 and NHS 111. However, calls made to 999 may be an overestimation, because

we cannot distinguish between 999 calls to the NHS and those for police, fire and coastguard services. On the other hand, using calls to NHS 111 may be an underestimation, because NHS 111 advice and triage services are available by phone and online. Moreover, there is a lack of robust data about resource use and costing of the NHS 111 services (Pope et al., 2017). Therefore, we chose to measure healthcare utilisation using the numbers of telephone/video and in-person consultations which was more readily interpretable in terms of healthcare utilisation and resource use.

Familiarity with social media

Familiarity with social media was captured by the question "on average, how long do you spend on social media sites per day". Documented answers include 10 to 30 minutes, 30 minutes to one hour, one to two hours, two to three hours, and more than three hours. From this question, we created a binary variable coded 1 to indicate the upper quartile of the daily use covering those using social media at least one hour per day (n=911) and 0 otherwise.

2.3. Statistical methods

We used Chi-squared analysis and cross-sectional regressions to examine the associations between individual health, healthcare utilisation and changes in physical activities during the first lockdown. We first conducted Chi-squared analysis to investigate differences between the higher and lower comorbidity groups. We then performed three sets of regression analysis to explore the cross-sectional relationships as depicted in Figure 1

Determinants of healthcare utilisation

To understand healthcare utilisation in the pandemic, we took numbers of consultations in person or by telephone/video as the dependent variables in the regressions. These regressions investigated the associations between healthcare utilisation, comorbidities, shielding and familiarity with social media (the blue region of Figure 1).

Determinants of physical activities

To understand changes of physical activities in the pandemic, we took changes in physical activities since the beginning of the lockdown as the dependent variable in the regression. This regression investigated the associations between changes in physical activities and comorbidities, shielding and familiarity with social media (the yellow region of Figure 1).

Self-reported health and mental health

To understand individual health status, we took self-reported health and mental health (feeling depressed/lonely) as the dependent variables in the regressions. We explored the association between health, comorbidities, consultations, changes in physical activities and familiarity with social media (the green region of Figure 1).

We used linear regressions for estimations with continuous dependent variables, numbers of telephone/video and in-person consultations. The Gauss-Markov assumptions were tested prior to the main analysis (Wooldrige, 2020): we tested multi-collinearity with the variance of inflation (Mansfield and Helms, 1982), normal distribution of the error terms with the Shapiro-Wilk test (Shapiro and Wilk, 1965) and homogeneity with the Breusch-Pagan test (Breusch and Pagan, 1979). Lower levels of variance of inflation (<5) were found among all variables, implying the estimations may not suffer from multi-collinearity. However, results

of the Shapiro-Wilk test and the Breusch-Pagan test indicated the violation to the normality and the homogeneity assumptions. Hence, ordinary least squares regressions were not suitable for our analysis. To relax the assumptions, we used generalised least squares regressions (Greene, 2012).

For ordinal dependent variables, including changes in physical activities, self-reported health and mental health, ordered logistic regressions were used to preserve the ordinal scale without sacrificing the statistical power. A necessary assumption for the ordered regression is the proportional odds assumption that the slope estimates should be consistent across the ordinal scale. The Brant test was used to test if the proportional odds assumption held (Brant, 1990). If the Brant test failed, the proportional odds assumption failed and thus generalised ordered logistic regressions were used. Generalised ordered regressions work in similar way as ordered regressions but relax the proportional odds restriction (Eluru, 2013). The result of the Brant test indicated that only changes in physical activities violated the proportional odds assumption ($p<0.001$). Hence, we utilised a generalised ordered logistic regression to estimate changes in physical activities. Other ordinal variables, self-reported health, feeling depressed and feeling lonely, did not violate the proportional odds assumption under the 95% confidence level (self-reported health: $p=1.00$; feeling depressed: $p=0.36$; feeling lonely: $p=0.59$). Thus, we estimated self-reported health and mental health with ordered logistic regressions.

Additional analyses were conducted to explore whether the impact of shielding on health care utilisation or physical activities differed between the higher and lower comorbidity groups. In

these further analyses we reran the regressions for healthcare utilisation or physical activities with an interaction term between a shielding notice and higher comorbidities.

3. Results

3.1. Between-group analysis

Table 1 presents the descriptive statistics of individuals in the lower and higher comorbidity groups along with the results of Chi-squared analysis. The percentage of individuals who received a shielding notice from the government in the higher comorbidity group was 8.44%, which was significantly higher than the 4.33% in the lower comorbidity group. The percentage of participants reporting poor health in the higher comorbidity group was 3.86% whilst that in the lower comorbidities group was only 1.28%. The percentage of participants reporting feeling depressed nearly every day in the higher comorbidity group was 1.93% and that in the lower comorbidities group was 0.81%. The percentage of participants reporting often feeling lonely in the higher comorbidity group was 5.79% and that in the lower comorbidities group was 3.43%.

3.2. Healthcare utilisation

Table 2 presents estimations regarding the associations between healthcare utilisation, comorbidities, shielding and familiarity with social media by using generalised least squares regressions. Model 1 and 3 are the baseline regressions on telephone/video and in-person consultations. The interactions between comorbidities and shielding were further included in Model 2 and 4.

An observation from Table 2 is that age was not significantly associated with telephone/video consultations but was significantly associated with in-person consultations. Moreover, this negative association between age and in-person consultations was found non-linear as indicated by the coefficients on age squared. Model 1 and Model 3 show that higher comorbidities were associated with telephone/video consultations but not necessarily with in-person consultations. A shielding notice was positively associated with both consultations and with greater reliance on telephone/video (0.6869) than that on in-person consultations (0.2945). In Model 2, the interaction between higher comorbidities and shielding was shown significant and negative. The lower Bayesian Information Criterion (BIC) of Model 2 (10,489.44) compared to Model 1 (10,494.11) implies a better goodness-of-fit with the interaction term in estimating the number of telephone/video consultations. Conversely, in Model 4, the interaction between higher comorbidities and shielding was not significant. The higher BIC of Model 4 (7,005.75) compared to Model 3 (6,998.26) implies a poorer goodness-of-fit with the interaction term in estimating the number of in-person consultations.

3.3. Changes in physical activities

Table 3 presents estimations regarding the associations between physical activities, comorbidities, shielding and familiarity with social media by using generalised ordinal logistic regressions. Model 5 presents the baseline results and Model 6 presents the estimation with the interaction between a shielding notice and higher comorbidities.

Results in Model 5 indicate that age is negatively associated with increases in physical activities during the lockdown period, but the association between age and decreases in physical activities was not found in our estimation. There is a significant association between

participants with higher comorbidities and increases in physical activities during the lockdown period. Conversely, familiarity with social media was positively associated with increases in physical activities and negatively associated with decreases in physical activities. In Model 6, the interaction term between a shielding notice and higher comorbidities was not significant. The higher BIC (8,307.48) also indicates a poorer goodness-of-fit of Model 6 compared to Model 5.

3.4. Self-reported health and mental health

Table 4 presents estimations regarding the associations between self-reported health/mental health, comorbidities, consultations and changes in physical activities by using ordered logistic regressions. Column 1-3 show the results of self-reported health, feeling depressed and feeling lonely respectively.

We found that age was positively associated with self-reported health but not necessarily with feeling depressed or feeling lonely. Individuals with higher comorbidities were more likely to have poorer self-reported health and more often to feel depressed or/and lonely during lockdown. Telephone/video consultations were negatively associated with self-reported health and positively associated with feeling depressed and feeling lonely. Conversely, in-person consultations do not present significant association with any health measures. Decreases in physical activities were associated with poorer self-reported health and increases in physical activities were associated with better self-reported health. Decreases in physical activities were associated with poorer mental health, but increases in physical activities did not link to better mental health.

4. Discussion

In this paper, we examined differences in healthcare utilisation, changes in physical activities, self-reported health and mental health between older individuals with higher and lower comorbidities during COVID-19. To explore how policy makers can mitigate the negative impacts, we investigated the effects of two policy instruments, social media and a shielding notice from the government.

We confirmed that older individuals with higher comorbidities were more likely to have poorer self-reported health and mental health. Whilst social distancing measures were effective in containing the spread of the virus, they also created social isolation among people (Armitage and Nellums, 2020, Wong et al., 2020). Social isolation has been a major public health concern due to its adverse outcomes in both physical and mental health (Courtin and Knapp, 2017). Being vulnerable to social isolation, older adults with higher comorbidities were more likely to experience these adverse outcomes during the pandemic.

The shielding notice issued by the government was found to be associated with more primary care use. Moreover, this shielding notice generated a greater reliance on telephone/video consultations compared to in-person consultations. This observation is consistent with the promotion of remote consulting in the UK to minimise interpersonal contact (Murphy et al., 2021, Flint et al., 2020). Model 2 shows a negative interaction between a shielding notice and higher comorbidities, indicating that the positive association between a shielding notice and telephone/video consultations was less strong for those with higher comorbidities.

Table 3 indicates that frequent use of social media raised the probability of increasing physical activities and reduced that of decreasing physical activities. This observation could be due to the role of social media in raising the awareness of health behavioural changes against COVID-19 (Al-Dmour et al., 2020). We therefore suggest that social media can be an effective instrument in promoting physical activities.

What lessons can policy makers take away from the first lockdown? Our research confirms the important role that physical activity plays in public health and the need to encourage physical activities throughout a lockdown. Initiatives that are effective at encouraging physical activities, through social media or other communications, have the potential to mitigate negative health consequences that may arise during a lockdown. Our research also suggest the need to consider issues of healthcare access, through telephone/video consultations, as well as through more traditional in-person consultations, not only during lockdowns but also as future ways to deliver effective care.

This paper is not without limitations. First, this paper offers a cross-sectional analysis and so cannot answer questions around changes in outcome variables overtime, and cannot confirm causality. Information on longitudinal patterns is needed to explore these variables over time and causal impact of COVID-19. Second, the sample was not necessarily representative, as the online nature of the survey required participants with some digital capacity. Third, the data were all self-reported. Our measures may deviate from the true values. Fourth, without adequate information on morbidities, we were not able to construct comorbidity indices, such as the Charlson Cormorbidity Index and the Elixhauser score (Austin et al., 2015), which are more commonly used in clinical practice. Fifth, our results of changes in physical activities

may be driven by the intensity of the activity. However, we were not able to detect this with our current data.

Finally, as more survey data becomes available overtime, we recommend that future research explores patterns of healthcare utilisation and physical activities for older individuals overtime as people adapted to the new lockdown regimes. These additional analyses will help to confirm the extent to which changes in lockdown measures impact on prolonged changes in healthcare utilisation and physical activities, providing additional insights for policy makers.

5. Conclusion

This paper highlighted (1) the association between individual health, healthcare utilisation and physical activities for older adults with comorbidities in COVID-19 pandemic; (2) effects of a shielding notice on health care usage; and (3) the potential for social media to mitigate negative health consequences arising in a lockdown. Higher comorbidities were associated with poorer self-reported health and mental health. We confirmed the importance of physical activities in public health and suggested the use of social media in promoting exercises during a lockdown. A shielding notice was related to more primary care use, with greater reliance on telephone/video consultations compared to in-person consultations. As COVID-19 pandemic continues to disrupt our routine life, further exploration is required to understand how we can cope with future lockdown or other restrictions.

References

AL-DMOUR, H., SALMAN, A., ABUHASHESH, M. & AL-DMOUR, R. 2020. Influence of social media platforms on public health protection against the COVID-19 pandemic via the mediating effects of public health awareness and behavioral changes: integrated model. *Journal of Medical Internet Research,* 22**,** e19996.

ARMITAGE, R. & NELLUMS, L. B. 2020. COVID-19 and the consequences of isolating the elderly. *The Lancet Public Health,* 5**,** e256.

ATKINS, J. L., MASOLI, J. A., DELGADO, J., PILLING, L. C., KUO, C.-L., KUCHEL, G. A. & MELZER, D. 2020. Preexisting comorbidities predicting COVID-19 and mortality in the UK biobank community cohort. *The Journals of Gerontology: Series A,* 75**,** 2224-2230.

AUSTIN, S. R., WONG, Y.-N., UZZO, R. G., BECK, J. R. & EGLESTON, B. L. 2015. Why Summary Comorbidity Measures Such As the Charlson Comorbidity Index and Elixhauser Score Work. *Medical Care,* 53**,** e65-e72.

BRANT, R. 1990. Assessing proportionality in the proportional odds model for ordinal logistic regression. *Biometrics***,** 1171-1178.

BREUSCH, T. S. & PAGAN, A. R. 1979. A simple test for heteroscedasticity and random coefficient variation. *Econometrica: Journal of the Econometric Society***,** 1287-1294.

CHAN, A. K., NICKSON, C., RUDOLPH, J., LEE, A. & JOYNT, G. 2020. Social media for rapid knowledge dissemination: early experience from the COVID-19 pandemic. *Anaesthesia,* 75**,** 1579-1582.

COURTIN, E. & KNAPP, M. 2017. Social isolation, loneliness and health in old age: a scoping review. *Health & Social Care in the Community,* 25**,** 799-812.

CREESE, B., BROOKER, H., ISMAIL, Z., WESNES, K. A., HAMPSHIRE, A., KHAN, Z., MEGALOGENI, M., CORBETT, A., AARSLAND, D. & BALLARD, C. 2019. Mild behavioral impairment as a

marker of cognitive decline in cognitively normal older adults. *The American Journal of Geriatric Psychiatry,* 27**,** 823-834.

EL-AWAISI, A., O'CARROLL, V., KORAYSH, S., KOUMMICH, S. & HUBER, M. 2020. Perceptions of who is in the healthcare team? A content analysis of social media posts during COVID-19 pandemic. *Journal of Interprofessional Care,* 34**,** 622-632.

ELURU, N. 2013. Evaluating alternate discrete choice frameworks for modeling ordinal discrete variables. *Accident Analysis & Prevention,* 55**,** 1-11.

FLINT, S. W., BROWN, A., TAHRANI, A. A., PIOTRKOWICZ, A. & JOSEPH, A.-C. 2020. Cross-sectional analysis to explore the awareness, attitudes and actions of UK adults at high risk of severe illness from COVID-19. *BMJ open,* 10**,** e045309.

GIJSEN, R., HOEYMANS, N., SCHELLEVIS, F. G., RUWAARD, D., SATARIANO, W. A. & VAN DEN BOS, G. A. 2001. Causes and consequences of comorbidity: a review. *Journal of Clinical Epidemiology,* 54**,** 661-674.

GREENE, W. H. 2012. The generalized regression model and heteroscedasticity. *Econometric Analysis***,** 257-289.

MANSFIELD, E. R. & HELMS, B. P. 1982. Detecting multicollinearity. *The American Statistician,* 36**,** 158-160.

MURPHY, M., SCOTT, L. J., SALISBURY, C., TURNER, A., SCOTT, A., DENHOLM, R., LEWIS, R., IYER, G., MACLEOD, J. & HORWOOD, J. 2021. Implementation of remote consulting in UK primary care following the COVID-19 pandemic: a mixed-methods longitudinal study. *British Journal of General Practice,* 71**,** e166-e177.

NOSEK, B. A., SIMONSOHN, U., MOORE, D. A., NELSON, L. D., SIMMONS, J. P., SALLANS, A. & LEBEL, E. P. 2017. *Standard Reviewer Statement for Disclosure of Sample, Conditions,*

Measures, and Exclusions [Online]. OSF. Available: osf.io/hadz3 [Accessed 24 August 2021].

POPE, C., TURNBULL, J., JONES, J., PRICHARD, J., ROWSELL, A. & HALFORD, S. 2017. Has the NHS 111 urgent care telephone service been a success? Case study and secondary data analysis in England. *BMJ open,* 7**,** e014815.

PUBLIC HEALTH ENGLAND. 2020. *Guidance on shielding and protecting people who are clinically extremely vulnerable from COVID-19* [Online]. Available: https://www.gov.uk/government/publications/guidance-on-shielding-and-protecting-extremely-vulnerable-persons-from-covid-19/guidance-on-shielding-and-protecting-extremely-vulnerable-persons-from-covid-19 [Accessed 24 August 2021].

SHAPIRO, S. S. & WILK, M. B. 1965. An analysis of variance test for normality (complete samples). *Biometrika,* 52**,** 591-611.

WONG, S. Y. S., ZHANG, D., SIT, R. W. S., YIP, B. H. K., CHUNG, R. Y.-N., WONG, C. K. M., CHAN, D. C. C., SUN, W., KWOK, K. O. & MERCER, S. W. 2020. Impact of COVID-19 on loneliness, mental health, and health service utilisation: a prospective cohort study of older adults with multimorbidity in primary care. *British Journal of General Practice,* 70**,** e817-e824.

WOOLDRIGE, J. M. 2020. Multiple Regression Analysis: Estimation. *Introductory Econometrics: A Modern Approach.* 7th ed.: Cengage Learning.

Table 1. Descriptive statistics and Chi-squared test for the differences between high and low comorbidity groups

Variables	All (n=3,807)	Lower comorbidities (n=2,978)	Higher comorbidities (n=829)	p
Age	66.77 (6.83)	66.02 (6.62)	69.47 (6.88)	<0.001
Number of comorbidities	0.85 (1.04)	0.39 (0.49)	2.48 (0.82)	<0.001
Female	79.64%	81.09%	74.43%	<0.001
Non-white	5.52%	5.24%	6.51%	0.15
Shielding notice	5.23%	4.33%	8.44%	<0.001
Self-reported health				
poor	1.84%	1.28%	3.86%	<0.001
fair	19.57%	15.95%	32.57%	<0.001
good	57.76%	59.13%	52.83%	<0.001
excellent	20.83%	23.64%	10.74%	<0.001
Feeling depressed				
never	67.61%	68.70%	63.69%	0.01
several days	29.03%	28.31%	31.60%	0.06
more than half of the days	2.31%	2.18%	2.77%	0.32
nearly every day	1.05%	0.81%	1.93%	0.01
Feeling lonely				
hardly ever	77.54%	78.58%	73.82%	<0.001
some of the time	18.52%	18.00%	20.39%	0.12
often	3.94%	3.43%	5.79%	<0.001
Change in physical activities				
increase	40.14%	42.34%	32.21%	<0.001
decrease	35.70%	33.61%	43.18%	<0.001
no change	24.17%	24.04%	24.61%	0.74
Tel/video consultations	0.43 (0.96)	0.40 (0.95)	0.56 (1.01)	<0.001
In-person consultations	0.16 (0.61)	0.15 (0.58)	0.20 (0.69)	0.11
Marital status				
married	67.09%	68.27%	62.85%	<0.001
widowed	7.35%	6.11%	11.82%	<0.001
separated	1.31%	1.04%	2.29%	0.01
divorced	10.40%	10.28%	10.86%	0.63
partnership	0.58%	0.50%	0.84%	0.25
co-habiting	5.86%	6.48%	3.62%	<0.001

single	7.41%	7.32%	7.72%	0.70
Education				
secondary	12.11%	11.35%	14.84%	0.01
post-secondary	11.22%	11.45%	10.37%	0.39
vocational	19.02%	18.54%	20.75%	0.15
undergraduate	35.36%	36.30%	31.97%	0.02
post-graduate	18.20%	18.40%	17.49%	0.55
doctorate	4.10%	3.96%	4.58%	0.43
Employment status				
employed (full time)	15.89%	17.63%	9.65%	<0.001
employed (part time)	17.73%	19.07%	12.91%	<0.001
self-employed	8.77%	9.94%	4.58%	<0.001
retired	55.14%	50.54%	71.65%	<0.001
unemployed	2.47%	2.82%	1.21%	0.01
Daily use of social media				
less than 10 mins	32.07%	31.43%	34.38%	0.11
10 - 30 mins	21.25%	21.96%	18.70%	0.04
30 mins - 1 hr	22.75%	23.27%	20.87%	0.15
1 - 2 hrs	15.55%	15.25%	16.65%	0.33
2 - 3 hrs	5.57%	5.14%	7.12%	0.03
more than 3 hrs	2.81%	2.96%	2.29%	0.31

Table 2. Associations between healthcare utilisation, comorbidities, shielding and familiarity with social media

	Telephone/video consultations		In-person consultations	
Variables	Model 1	Model 2	Model 3	Model 4
Age	-0.0444	-0.0440	-0.0700***	-0.0699***
	(0.0327)	(0.0327)	(0.0207)	(0.0207)
Age squared	0.0003	0.0003	0.0005***	0.0005***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Higher comorbidities	0.1228***	0.1607***	0.0364	0.0422*
	(0.0383)	(0.0397)	(0.0242)	(0.0251)
Shielding	0.6869***	0.8674***	0.2945***	0.3220***
	(0.0697)	(0.0858)	(0.0440)	(0.0543)
Familiarity with social media	0.0246	0.0199	0.0361	0.0354
	(0.0365)	(0.0365)	(0.0231)	(0.0231)
High comorbidities × Shielding		-0.5246***		-0.0802
		(0.1461)		(0.0925)
BIC	10,494.11	10.489.44	6,998.26	7,005.75

All regressions are adjusted for gender, ethnicity and education.
Standard errors are in parenthesis. *p<0.10, **p<0.05,***p<0.01.

Table 3. Associations between changes in physical activities, comorbidities, shielding and familiarity with social media

	Model 5		Model 6	
Variables	Increase	Decrease	Increase	Decrease
Age	-0.2735***	-0.0610	-0.2717***	-0.0577
	(0.0791)	(0.0785)	(0.0790)	(0.0785)
Age squared	0.0022***	0.0006	0.0022***	0.0005
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Higher comorbidities	0.3352***	-0.0193	0.3237***	0.0080
	(0.0859)	(0.0944)	(0.0885)	(0.0973)
Shielding	-0.3352**	-0.1445	0.3036	-0.0033
	(0.0859)	(0.1761)	(0.1939)	(0.2109)
Familiarity with social media	0.1959**	-0.2211**	0.1970**	-0.2236**
	(0.0801)	(0.0935)	(0.0802)	(0.0935)
High comorbidities × Shielding			0.2477	-0.4366
			(0.3597)	(0.3828)
BIC	8,293.63		8,307.48	

All regressions are adjusted for gender, ethnicity and education.
Standard errors are in parenthesis. *p<0.10,**p<0.05,***p<0.01.

Table 4. Association between self-reported health, depression and loneliness with comorbidities, consultations, changes in physical activities and familiarity with social media

Variables	Self-reported health	Depressed	Lonely
Age	0.1633**	-0.1055	0.0042
	(0.0692)	(0.0749)	(0.0843)
Age squared	-0.0011**	0.0006	-0.0001
	(0.0005)	(0.0006)	(0.0006)
Higher comorbidities	-0.9168***	0.2766***	0.2680***
	(0.0820)	(0.0863)	(0.0955)
Tel/video consultations	-0.4187***	0.2329***	0.1724***
	(0.0377)	(0.0362)	(0.0395)
In-person consultations	-0.0278	-0.0978	-0.0219
	(0.0582)	(0.0610)	(0.0636)
Change in physical activities			
increase	0.2431***	-0.0414	0.0058
	(0.0834)	(0.0945)	(0.1103)
decrease	-0.7907***	0.5291***	0.6477***
	(0.0870)	(0.0933)	(0.1057)
Familiarity with social media	-0.4252***	0.4113***	0.3936***
	(0.0771)	(0.0802)	(0.0882)
BIC	7,426.60	5,710.33	4,786.48

All regressions are adjusted for gender, ethnicity and education.
Standard errors are in parenthesis. *p<0.10, **p<0.05,***p<0.01.

Figure 1. Associations between comorbidities, shielding, familiarity with social media, physical activities, healthcare utilisation and health