**Associations between self-reported healthcare disruption due to COVID-19 and avoidable hospitalisation: Evidence from seven linked longitudinal studies for England**

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**Abstract**

**Objectives:** The aim of our paper is to examine whether there is an association between individuals experiencing disrupted access to healthcare during the COVID-19 pandemic and risk of an avoidable hospitalisation.

**Design:** Observational analysis using individual-level survey data for England from seven longitudinal cohort studies linked to electronic health records from NHS Digital within the UK Longitudinal Linkage Collaboration trusted research environment.

**Setting:** England

**Participants:** Individual-level records for 29 276 people.

**Main outcome measures:** Avoidable hospitalisations were defined as emergency hospital admissions for ambulatory care sensitive and emergency urgent care sensitive conditions (1st March 2020 to 25th August 2022).

**Results:** 35% of people self-reported that they experienced some form of disrupted access to healthcare during the COVID-19 pandemic. Those whose access was disrupted were at increased risk of any (Odds Ratio (OR) = 1.80, 95% Confidence Intervals (CIs) = 1.39 to 2.34), acute (OR = 2.01, CIs = 1.39 to 2.92) and chronic (OR = 1.80, CIs = 1.31 to 2.48) ambulatory care sensitive hospital admissions. Individuals who experienced disrupted access to appointments (e.g., visiting their GP or an outpatient department) and procedures (e.g., surgery, cancer treatment) were positively associated with measures of avoidable hospitalisations as well.

**Conclusions:** Our study presents novel evidence from linked individual-level data showing that people whose access to healthcare was disrupted were more likely to have an avoidable or potentially preventable hospitalisation. Our findings highlight the need to increase healthcare investment to tackle the short- and long-term implications of the pandemic, as well as protect treatment and procedures during future pandemics.

**Keywords**

COVID-19; avoidable hospitalisations; linked data; cohort; healthcare; disruption; UK LLC.

**Summary box**

**What is already known on this topic**

A large literature has described the extent of disruption in accessing healthcare services and treatment during the COVID-19 pandemic. We are not aware of any research that has evaluated if experiences of disruption were associated with negative health outcomes.

**What this study adds**

Individuals who experienced disrupted access to healthcare during the COVID-19 pandemic were more likely to have an avoidable and potentially preventable hospital admission. Disrupted access to appointments and procedures, but not medications, were important pathways for explaining this association. Our findings demonstrate the importance of reducing the backlog of COVID-19 disruption to tackle the short- and long-term implications of the pandemic.

**Introduction**

The COVID-19 pandemic created unprecedented disruption to healthcare in the UK. Health facilities reoriented to care for surging numbers of patients with COVID-19, initially through postponing or cancelling non-emergency treatment and diagnostic tests (1). People were deterred from seeking healthcare by: fear of being exposed to SARS-CoV-2 in health facilities (2), altruistic behaviours aimed at ‘protecting’ the NHS (3), and reduced availability of face-to-face consultations (4). Collectively, these phenomena have resulted in fewer GP consultations (5,6), diagnostic tests (6,7), cancer referrals, diagnoses and treatments (5,8,9), cardiovascular treatment and surgery (10), elective and emergency hospital admissions (11–13), and increased waiting times to initiate treatment (14). There have also been more people dying at home during the pandemic (15), with changes in secondary care seeking behaviours potentially impacting these trends. Although these impacts are not unique to the UK (16–20), it has fared much worse than many otherwise similar countries.

The extent of healthcare disruption has been described elsewhere (21), but to our knowledge this has not been linked to empirically observed adverse health outcomes at the individual level. It is plausible that delays in diagnosis and treatment allow illnesses to progress to greater severity. The aim of our paper is to examine whether there is an association between individuals experiencing disrupted access to healthcare during the pandemic and risk of an avoidable hospitalisation. Avoidable hospitalisations are unplanned admissions that could potentially have been prevented through timely care delivered in the community. The concept is used as a ‘warning sign’ for failings in health system performance and is a key metric used in the NHS (22–25). We hypothesize that people whose care was disrupted during the pandemic would be more likely to have an avoidable hospitalisation. Given that pandemic-disruption has affected the lives of everyone, this approach allows us to evaluate the overall impact of disruption rather than focusing on discrete services whose study may obscure the overall effect of society-wide disruption.

It is difficult to capture the individual experience of healthcare disruption from electronic health records, but it can be identified in longitudinal surveys. By linking data on participants in longitudinal cohorts with their electronic health records, we can describe the impact of any disruption they experience on health outcomes at an individual level. We are not aware of any research that has used linked individual-level data to study the effects of COVID-19 healthcare disruption.

**Methods**

*Data*

We used data on individuals from seven UK population-based longitudinal studies linked to electronic health records from NHS Digital for England. These included five birth cohorts (1946 National Survey of Health and Development, 1958 National Child Development Study, 1970 British Cohort Study, Next Steps and Millennium Cohort Study) and two age-heterogenous studies (English Longitudinal Study of Ageing and Understanding Society). Each cohort is described in Appendix Table S. The cohort data were accessed using the UK Longitudinal Linkage Collaboration (UK LLC). The UK LLC trusted researcher environment hosts de-identified data from many longitudinal population studies and systematically links these to participants’ health, administrative and environmental records within a secure analysis environment. Ethical approval for the project was granted by the University of Liverpool’s Research Ethics Board (reference 10634).

Each cohort study sent surveys to members of their cohorts inquiring about their experiences during the COVID-19 pandemic, supplementing their pre-pandemic data collection processes. The data from all participants who responded to these surveys across the cohorts were pooled, giving a total sample size of 41 439 (persons). Combining cohorts brings value through improving the representativeness of the data and increasing statistical power (21). We excluded people residing outside England as data linkage was not possible (n = 5975). We further excluded individuals who did not consent to linkage or for whom linkage was not possible (n = 5911). We excluded all individuals who died during the study period (n = 277). The total analytical sample size was n = 29 276 (Appendix Table A breaks down sample sizes by cohort).

*Outcomes*

Linkage of cohort members to electronic health records was conducted by the UK LLC. Electronic health records from NHS Digital included civil registration of deaths, secondary care (hospital episode statistics admitted patient care), and vaccination status. We selected records between 1st March 2020 (which we define as the start of NHS disruption) and 25th August 2022 (end of available data), which thus comprise the study period.

We selected two measures of unplanned avoidable hospitalisations commonly used for evaluating NHS performance: Ambulatory Care Sensitive (ACSC) and Emergency Urgent Care Sensitive (EUCS) conditions (22,23). ACSC are conditions that can be, in theory, treated through community care and therefore should not require a hospital admission (23,26). We used an overall measure for any ACSC, as well as stratified by ACSC type into (i) acute (e.g., cellulitis, dental caries, rickets, gastric ulcer), (ii) chronic (e.g., hypertension, angina, asthma), (iii) vaccine-preventable conditions (e.g., mumps, measles, influenza). EUCS are acute exacerbations of urgent conditions that will potentially result in hospital admission, but that the NHS should be trying to treat within the community to minimise the need for hospital care (23,26). Code lists were designed to match NHS Digital’s approach (openly available at <https://www.opencodelists.org/users/mgreen/>) and we selected any emergency hospital admission during the study period where codes were present in the primary diagnosis field. COVID-19 was not included in this definition of avoidable hospitalisations. We also collected an outcome of whether an individual had any hospital admission during the study period to contextualise our findings. This gave us a total of six outcome variables that we considered in the main analyses. All outcome variables in the main analysis were binary outcomes.

We also used COVID-19 vaccination status (binary: individual had received two COVID-19 doses by the end of the study period or not) as an outcome variable in a falsification test (27,28). We did not expect there to be an association between experiences of healthcare disruption and vaccination uptake, because vaccine delivery was prioritised and therefore less disrupted. It therefore provides an imperfect, but valuable, instrumental indicator to assess the role of unobserved confounding in our models. We hypothesised that if there were any residual confounding, we would find an association here since it would confound our exposure and falsification variables in similar ways.

*Exposures*

Our primary exposure variable was whether individuals self-reported any disruption to healthcare (i.e., cancelled or postponed care, changes to planned/existing treatments). This was measured across all waves of data collection. This was based on questions asked in each longitudinal population study about participants’ experiences of health care during the pandemic. Disruption was defined either where (i) the question explicitly asked about experiences of disruption in accessing health services, or (ii) where people had appointments, treatment or surgery booked and participants reported that they were changed, postponed or cancelled. We further stratified our exposure by type of disruption into (i) appointments (e.g., visiting their GP or an outpatient department), (ii) procedures (e.g., surgery, cancer treatment), and (iii) medications. This allowed us to examine the different pathways through which disruption affected individuals. Descriptions of questions asked in surveys and how they were harmonised are reported in Appendix Table B.

*Control variables*

We adjusted for the longitudinal cohort that individuals were in (categorical variable). Variables were selected only of those consistent and comparable across longitudinal population studies, limiting the measures we could include (see Appendix Table A for full description of this harmonisation process). We selected the most recent value for each measure during the COVID-19 waves (although selecting older responses did not change the man findings). Personal characteristics of age (numeric), sex (male or female), and ethnicity (White or ethnic minority) were included to account for demographic differences. Age was included both as a linear and quadratic term to account for the non-linear increase in risk of hospitalisation with age. Racially minoritized ethnic groups often face structural barriers in accessing health care, with avoidable hospitalisations being higher for some ethnic groups (24,29). The inconsistent ethnic categorisations used meant that we had to amalgamate into a simplistic binary definition. Socioeconomic position was measured using housing tenure (defined as (i) owned house outright/with mortgage, and (ii) renting (social or private) or other tenure) and neighbourhood socioeconomic deprivation (2019 index of multiple deprivation quintile provided via linkage by NHS Digital). Including multiple measures of socioeconomic position is important to capture different dimensions of social stratification. Tenure accounts for accumulated wealth and neighbourhood deprivation measures for the broader socioeconomic context of an individual’s life. Both measures have been demonstrated to be independently associated to health outcomes including avoidable hospitalisations (23,30,31).

Adequately measuring health and comorbidity was pertinent since sicker individuals are likely to be at greater risk of hospital admissions. Adjusting for health status is complex and we account for multiple aspects. Comorbidity was measured using Charlson Comorbidity Index with Quan weights calculated from hospital episode statistics one-year pre-pandemic (1st March 2019 to 29th February 2020) (32). The Charlson Comorbidity Index describes the extent of comorbidity of people across 16 health conditions and is predictive of mortality (32), as well as ambulatory care sensitive conditions (33,34). Self-rated health status (excellent/good or fair/poor) was included as an indicator of physical health. It is associated with objective health outcomes including mortality (35–37) and avoidable hospitalisations (38,39). While health status may sit on our causal pathway between disruption and health outcomes (e.g., people with poor health are not only more likely to have an avoidable hospital admission, but may require greater healthcare needs making them more exposed to the effects of disrupted access of healthcare), we treat it here as a key confounder which needs to be adjusted for.

We also assessed alternative health and comorbidity outcomes as sensitivity analyses. The Elixhauser Index was used as an alternative to the Charlson Comorbidity Index to avoid relying on a single composite index (40). Presence or absence of four self-reported health conditions (asthma, cancer, diabetes and hypertension) were also included as covariates to measure comorbidity. As records were collected during the COVID-19 surveys, we cannot be sure that they were present before experiences of disruption. We include these as sensitivity analyses since they may act as mediators.

*Statistical analyses*

Descriptive statistics were calculated to provide summary measures of our data. In the main analyses, we used logistic regression models since our six outcome variables were all binary outcomes. For each outcome, we ran two logistic regression models: (i) an unadjusted model where the exposures were the only independent variables, and (ii) a fully adjusted model that includes all exposures and control variables together. Model coefficients were converted to odds ratios to aid the interpretation of associations and we present these data visually.

In the main analysis, we considered any outcome during the study period since we are unsure when experiences of disruption occurred (individuals were only asked to report if they had experienced disruption at any point). Three sensitivity analyses were undertaken to assess how robust this modelling framework was. First, we limited our six outcome variables to only hospital admissions which took place after the final survey date so that we are certain that avoidable hospitalisations happened after experiences of disrupted access to healthcare. Here we also use the same logistic regression model specification from the main analyses for our six outcomes. Second, we used a Cox regression model as an alternative method for modelling each of the six outcomes. Rather than use a binary measure of if a person had an avoidable hospitalisation, we use a time to outcome measured from the last survey date. This was because the follow-up time is not consistent across participants due to differences in the last survey date. Third, we used a logistic regression model to predict whether a person was vaccinated or not (binary outcome). This was undertaken as a falsification test to assess potential residual confounding in our model, since many shared confounders are likely to apply to this outcome (e.g., people who are more likely to seek healthcare are more likely to be both vaccinated and to experience hospitalisations).

All analyses accounted for the sampling design of each survey, including sample weights that account for representativeness, attrition, and non-response (i.e., sample weights, primary sampling units, strata and finite population correction factor were adjusted for). The numbers of missing data across our variables are presented in Appendix Table C. Missing values for each variable were imputed using polytomous regression using all other exposure and control variables. We also report analyses using only complete cases as a sensitivity analysis. Model assumptions for both types of regression models were checked and we did not identify any problematic issues. All analyses were conducted using R statistical software and the code is openly available (<https://github.com/markagreen/healthcare_disruption_LLC>).

*Patient and public involvement (PPI)*

No specific engagement for the project. Feedback on the remit of the project and a lay abstract was provided from PPI groups as part of the UK LLC data access application review process. This helped to refine our research question which was previously unclear, as well as how to communicate the problem we were addressing.

**Results**

*Main analyses*

Table 1 presents summary statistics of our analytical sample. Each of our outcomes were uncommon during our study period. By 25th August 2022, 14% (weighted percentage) of participants had a hospital admission. 3% of participants were admitted for an ambulatory care sensitive condition. Among these admissions, vaccine-preventable admissions were the least common (0.8%). 35% of participants reported experiencing any form of disruption in their access to healthcare due to COVID-19. Disruption was most commonly experienced in accessing appointments (26%), followed by procedures (18%). Few individuals experienced disruption in their access to medications (6%). Summary statistics for control variables are presented in Table 2. Participants who experienced some form of disrupted access to healthcare were older, had poorer health and were more likely to reside in the most deprived areas. Participants with linked data experienced more disruption than those with unlinked data, although differences were only small (1-2% more) and therefore are unlikely to strongly bias our observations (Appendix Table D). Missing data were higher for disrupted access to medications (30.5%) and procedures (18.8%) (Appendix Table C).

**Table 1: Descriptive statistics for outcome variables and exposures in the pooled sample.**

|  |  |  |  |
| --- | --- | --- | --- |
| Measure | Frequency | Unweighted Percentage | Weighted\* Percentage |
| Total admissions | 3618 | 12.36 | 13.65 |
| Ambulatory care sensitive any | 780 | 2.66 | 3.36 |
| Ambulatory care sensitive acute | 347 | 1.19 | 1.32 |
| Ambulatory care sensitive chronic | 369 | 1.26 | 1.39 |
| Ambulatory care sensitive vaccine preventable | 94 | 0.32 | 0.78 |
| Emergency urgent care sensitive | 625 | 2.13 | 2.37 |
| Two COVID-19 vaccine doses | 27513 | 93.98 | 92.64 |
| Disruption - any | 9742 | 33.28 | 34.79 |
| Disruption to appointments | 7456 | 25.47 | 26.20 |
| Disruption to medications | 1568 | 5.36 | 5.86 |
| Disruption to procedures | 5292 | 18.08 | 18.12 |
| \* Values were adjusted for the sample structure of each longitudinal study |

**Table 2: Descriptive statistics for how our control variables differed by whether participants had experienced any form of disrupted access to healthcare or not.**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Measure** |  | **Total** |  | **Any disruption** |  | **No disruption** |
| **Frequency** | **Unweighted value** | **Weighted value** | **Frequency** | **Unweighted value** | **Weighted value** | **Frequency** | **Unweighted value** | **Weighted value** |
| Main analyses |  |  |  |  |  |  |  |  |  |
| Age – mean (std dev) |   | 52.9 (18.6) | 52.9 (19.5) |   | 57.9 (17.5) | 59.6 (17.6) |  | 50.4 (18.6) | 49.4 (19.6) |
| Female - % | 15721 | 53.7 | 48.5 | 5334 | 54.8 | 50.7 | 10387 | 53.2 | 47.3 |
| Male - % | 13555 | 46.3 | 51.5 | 4253 | 43.7 | 49.3 | 9302 | 47.6 | 52.7 |
| White - % | 26760 | 91.4 | 92.4 | 8835 | 90.7 | 93.1 | 17925 | 91.8 | 92.0 |
| Not White - % | 2516 | 8.6 | 7.6 | 752 | 7.7 | 6.9 | 1764 | 9.0 | 8.0 |
| Do not own home - % | 14565 | 50.1 | 49.5 | 4648 | 47.7 | 47.1 | 9917 | 50.8 | 50.7 |
| Own home - % | 14711 | 49.9 | 50.5 | 4939 | 50.7 | 52.9 | 9772 | 50.0 | 49.3 |
| Poor health - % | 6202 | 78.8 | 24.3 | 3354 | 34.4 | 38.7 | 2848 | 14.6 | 16.9 |
| Good health - % | 23074 | 21.2 | 75.7 | 6233 | 64.0 | 61.3 | 16841 | 86.2 | 83.1 |
| IMD Quintile 1 - Most Deprived % | 3638 | 12.4 | 16.4 | 1237 | 12.7 | 18.8 | 2401 | 12.3 | 15.2 |
| IMD Quintile 2 - % | 4784 | 16.3 | 17.8 | 1651 | 16.9 | 18.5 | 3133 | 16.0 | 17.5 |
| IMD Quintile 3 - % | 6038 | 20.7 | 20.1 | 1988 | 20.4 | 20.1 | 4050 | 20.7 | 20.0 |
| IMD Quintile 4 - % | 7144 | 24.4 | 22.4 | 2331 | 23.9 | 21.3 | 4813 | 24.6 | 22.9 |
| IMD Quintile 5 - Least Deprived - % | 7672 | 26.2 | 23.4 | 2380 | 24.4 | 21.3 | 5292 | 27.1 | 24.4 |
| Charlson Comorbidity Index – mean (std dev) |  | 0.1 (0.5) | 0.1 (0.5) |  | 0.2 (0.7) | 0.2 (0.7) |  | 0.1 (0.4) | 0.1 (0.4) |
| Sensitivity analyses |  |  |  |  |  |  |  |  |  |
| Elixhauser Index – mean (std dev) |  | 0.2 (0.7) | 0.2 (0.8) |  | 0.4 (1.0) | 0.5 (1.0) |  | 0.1 (0.5) | 0.1 (0.5) |
| Asthma - % | 3044 | 10.4 | 10.7 | 1193 | 12.2 | 13.1 | 1851 | 9.5 | 9.5 |
| Cancer - % | 833 | 2.8 | 2.6 | 482 | 4.9 | 4.7 | 351 | 1.8 | 1.5 |
| Diabetes - % | 1637 | 5.6 | 6.7 | 898 | 9.2 | 10.9 | 739 | 3.8 | 4.6 |
| Hypertension - % | 4398 | 15.0 | 17.2 | 1941 | 19.9 | 25.1 | 2457 | 12.6 | 13.1 |

\* Values were adjusted for the sample structure of each longitudinal study.

Note: Percentages (%) were presented for categorical or binary measures. Mean was presented for numerical or continuous measures (as well as standard deviation (std dev)).

Figure 1 (see Appendix Table E for full model output) presents results from a series of logistic regression models relating experiences of healthcare disruption to each of our six outcome variables. We found positive associations between experience of healthcare disruption and five of our outcomes in the unadjusted models, with no clear association detected to vaccine-preventable ambulatory care sensitive hospital admissions. Following adjustment for known explanatory factors, positive associations remained for four outcomes and were attenuated for emergency urgent care sensitive hospital admissions. People who experienced any form of healthcare disruption had 80% higher odds of being admitted to hospital for any ambulatory care sensitive condition (Odds Ratio (OR) = 1.80, 95% CIs = 1.39 to 2.34), two times higher odds of being admitted for an acute ambulatory care sensitive condition (OR = 2.01, CIs = 1.39 to 2.92), and 80% higher odds of being admitted for a chronic ambulatory care sensitive condition (OR = 1.80, CIs = 1.31 to 2.48). We also find that people who between experienced disrupted access to healthcare had 82% higher odds (OR = 1.82, CIs = 1.55 to 2.14) of being hospitalised during the study period.



**Figure 1: Model summary statistics for a logistic (binomial) regression exploring associations between experiences of healthcare disruption and whether an individual had an avoidable hospitalisation. Note: Model adjustment includes the following variables: age, age-squared, sex, ethnicity, housing tenure, self-rated health status, Charlson Comorbidity Index and longitudinal cohort).**

We next investigated how the type of healthcare disruption experienced was associated to our six outcome variables (Figure 2, see Appendix Table F for full model output). Individuals who experienced disrupted access to procedures had 77% higher odds of being admitted to hospital for any ambulatory care sensitive condition (OR = 1.77, CIs = 1.30 to 2.41), 88% higher odds of being hospitalised for a chronic ambulatory care sensitive condition (OR = 1.88, CIs = 1.28 to 2.75), 45% higher odds for an emergency urgent care sensitive admission (OR = 1.45, CIs = 1.05 to 1.99), and 57% higher odds for any hospital admission (OR = 1.57, CIs = 1.28 to 1.92). Individuals who experienced disruption in accessing appointments had 52% higher odds (OR = 1.52, CIs = 1.09 to 2.12) of a hospital admission for any ambulatory care sensitive condition and 46% higher odds (OR = 1.46, CIs = 1.21 to 1.75) of any hospital admission. Finally, individuals who experienced disrupted access to medications had more than two-times higher odds of being admitted to hospital for any ambulatory care sensitive condition (OR = 2.29, CIs = 1.02 to 5.10), although the confidence intervals were wide suggesting some caution in interpreting this result. We did not find any clear associations between this type of disruption and any other outcome.



**Figure 2: Model summary statistics for a logistic (binomial) regression exploring associations between experiences of three types of healthcare disruption (procedures, medications and appointments) and whether an individual had an avoidable hospitalisation (by type). Model adjustment includes the following variables: age, age-squared, sex, ethnicity, housing tenure, whether had COVID-19, self-rated health status, Charlson Comorbidity Index and longitudinal cohort). Results for vaccine-preventable ambulatory care sensitive conditions and disruption to medications were not robust due to small number issues.**

*Sensitivity analyses*

We excluded all hospital admissions that occurred before the last survey date to ensure that our exposures occurred before each outcome. Summary statistics for these outcome variables are presented in Appendix Table G. Irrespective of the statistical model used, the analyses were in agreement with the analyses presented in the main analyses (Appendix Tables H to K). The main difference was that the Cox regression model detected a greater number of associations between the exposures and outcomes. These additional associations were always positively associated to each outcome.

We assessed the impact of controlling for additional health measures on our findings. Replacing the Charlson Comorbidity Index with the Elixhauser Index did not materially change any associations (Appendix Tables L and M). When we additionally controlled for asthma, cancer, diabetes and hypertension as control variables, the findings were in agreement with the main analyses (Appendix Tables N and O). These analyses suggest that our analyses were robust to alternative specification of controlling for health.

We investigated whether our measures of healthcare disruption were associated with COVID-19 vaccination uptake as a falsification test (Appendix Table P). Looking at overall experiences of healthcare disruption, we found a positive association in unadjusted analyses which was attenuated post-adjustment. When considering type of healthcare disruption, we again detected associations in unadjusted analyses that disappeared following adjustment. This suggests a low risk of residual confounding in our fully adjusted associations.

Finally, we re-ran our main analyses for only complete cases. When considering any experience of disrupted access to healthcare, associations to any and acute ambulatory care sensitive admissions, and any hospital admission were consistent (Appendix Tables Q). There was a reduction in the point estimate to chronic ambulatory care sensitive admissions (OR = 1.48, CI = 0.93 to 2.36). The model detected an association to vaccine-preventable ambulatory care sensitive admissions (OR = 2.44, CI = 1.15 to 5.21), although the confidence intervals were wide. We next examined differences to analysing type of healthcare disruption (Appendix Table R). Point estimates were in relative agreement to the main analyses. The model also detected a positive association between disruption to procedures and acute ambulatory care sensitive admissions (OR = 1.58, CIs = 1.03 to 2.44).

**Discussion**

*Key results*

Our study presents the first empirical investigation utilising linked individual-level data to examine the impacts of healthcare disruption on avoidable hospitalisations. We estimated that 35% of people in England experienced disrupted access to healthcare, with disruption to appointments (e.g., seeing a GP or healthcare professional) being most common. Overall, individuals who reported any form of disruption in accessing healthcare were more likely to have been admitted to hospital for an avoidable or potentially preventable condition between 1st March 2020 and 25th August 2022. We found an 80%, two times and 80% increase in the odds of hospitalisation for any, acute and chronic ambulatory care sensitive conditions respectively. Individuals who reported disruption in accessing medications or appointments were more likely to be hospitalised for any ambulatory care sensitive conditions. Individuals who reported disruption in accessing procedures were more likely to be hospitalised for any, chronic ambulatory care sensitive or emergency urgent care sensitive conditions.

*Interpretation*

There are several potential explanations for why disrupted access to healthcare was associated with avoidable hospitalisations. Appointments with healthcare professional provide people with opportunities to seek advice, access secondary care, receive diagnostic tests, and receive treatment (5,6,19). Disruptions may delay care that is needed, with people needing hospitalisation as diseases progress (for example, presenting at later disease stages that are harder to treat). In particular, sudden changes in health often prompt people to seek a consultation (41), which may explain why we found an association with any ambulatory care sensitive conditions. Similarly, disruptions to procedures (e.g., surgery, treatment) may lead to exacerbations of existing and longer-term conditions, or disease progression that would otherwise have been treated (16,20,23). This may be why we find that associations to chronic ambulatory care sensitive conditions. We are cautious about drawing too many conclusions from our data about what should be done to prevent disruptions. However, our finding on the importance of disrupted access to procedures as being associated to avoidable hospitalisations is intuitive. Treatment and surgeries are less easy to deliver safely during a pandemic, whereas consultations and access to medications can be undertaken remotely, especially given the opportunities of online working. Future research should tease out these specific pathways where disruption leads to an avoidable hospitalisation to identify mechanisms that could mitigate the effects of disruption of services.

Few people experienced problems with obtaining medications (6%), which were also rarely associated with avoidable hospitalisations. Our findings may suggest that medicines supply was resilient during the pandemic. Even during periods of greatest disruption, when there were lockdowns, pharmacies were deemed essential services and remained open in the UK. While they did experience some issues with staff sickness and medicine shortages (42), they adapted successfully, aided by remote GP consultations and home deliveries (4). Other evidence has suggested that while repeat prescriptions were not affected by the pandemic, the rate of new prescriptions in England fell by 30% (6). It is also possible that the greater disruption in accessing GP appointments led to reduced opportunities for iterative adjustments of medication regimes reducing treatment effectiveness. This may have influenced risk of avoidable hospitalisation.

Our findings demonstrate the need to increase investment in the health system to counter the negative effects of healthcare disruption resulting from the COVID-19 pandemic. While NHS activity has returned to some extent, it has not returned to 2019 levels (29) and the NHS has struggled to clear the backlog of treatments, diagnostic tests, procedures and appointments (43). More recent disruption during winter 2022-23, with low rates of staff retention, chronic underfunding, healthcare worker strikes, high levels of staff illness, high prevalence of influenza and COVID-19, and persisting waiting lists have compounded the pandemic-related disruption (43,44). The challenging economic context of high inflation and Brexit has not however, been met with the political will to increase funding currently. This has placed the NHS in an almost impossible situation as it seeks to tackle its legacy of underinvestment in labour and capital, both critical in responding to the longer-term impacts of healthcare disruption due to the pandemic (5).

*Strengths and limitations*

Our study has several strengths. We combined data from seven individual-level longitudinal studies which are drawn from independently nationally representative samples. Using only a single study would have restricted our sample size for events or limited analyses to certain demographic groups. The ability to systematically link self-reported data on disruption experienced to participant’s electronic health records within the UK Longitudinal Linkage Collaboration has been crucial to overcome previous barriers of linking survey data with health records (45). By combining individual-level longitudinal studies and electronic health records we complement their individual strengths (i.e., depth of context about individuals alongside objective hospital admissions data). Importantly, our results contrast with research using electronic health records alone, which showed falls in avoidable hospitalisations during periods of greatest disruption (29). These different insights demonstrate how analysis of population level routine records can be misleading where they don’t have the same level of detail linked individual-level survey data often contain.

Our analyses are observational and have limited ability to draw causal inferences. While our measures of healthcare disruption were specifically asked as part of surveys about experiences of the pandemic, we did not have any data on pre-pandemic experiences of any difficulties in accessing health care. Pre-pandemic disruption to accessing healthcare across the NHS was minimal when compared to the unprecedented nature and extent of disruption the pandemic brought in accessing healthcare suggesting that our measures on experiences of this disruption are valid. We are unable to link specific experiences of disruption to particular adverse events, and not all avoidable hospitalisations will be due to the disruption of care. The measured outcomes may have not occurred after our ‘exposures’ in our main analysis, although sensitivity analyses restricted analyses to only outcomes after the exposures which suggested little difference in the findings. Our exposure measures were self-reported and may be subject to biases. For example, “plaintive set” can influence self-reported measures and may have inflated reports of exposure to disruption. In the situation where this reporting bias also influences outcome measures in the same direction biased associations can arise. Hospital admission depends on an individual presenting to a health facility and complaining of their condition. We have shown elsewhere that this can lead to bias (46), although this may have been less of a risk during our study given the general reluctance of hospitals to admit patients during the study period (29).

Inconsistency of measures across cohorts limited our ability to control for potential confounders. Exclusion through non-participation in surveys may have introduced bias in our sample. Pooling independently representative birth cohorts and age-heterogenous longitudinal population studies together may not generate a representative pooled sample (e.g., birth cohorts may introduce over-representation of some ages). Our pooled sample under-represented people from ethnic minority backgrounds and more deprived areas. This may be partly explained by four of the seven longitudinal population studies targeting middle aged or older adults. However, we applied sample weights and even non-representative studies tend not to show differences in their estimates of associations (47). There may be some bias introduced by data linkage due to incomplete or incorrect matching (45,48), which may disproportionately impact on marginalised groups and people who may have migrated to other parts of the UK. Biases may have been introduced where study participants did not consent to linkage to their health records (48), although the impacts on our exposures was limited (Appendix Table D). Missing data were also moderate for some exposures (e.g., disrupted access to medications was 30.5%) which may have introduced bias, although imputed and complete case analyses produced similar findings. Due to the rarity of our outcome variables, we were unable to explore whether experiences of healthcare disruption were greater in particular population subgroups (e.g., by ethnicity or deprivation). This is pertinent since the topics we examine are not evenly felt across the UK. For example, healthcare disruption was disproportionately experienced in socioeconomically deprived communities (5,11,21), with avoidable hospitalisations also higher in deprived areas (49). The rarity of our outcomes produced wide confidence intervals so that, even with a large pooled sample, power is limited. Exploring how disrupted access to healthcare mediated the relationship between social inequalities and health is an important research gap.

Unplanned hospitalisations may only occur after a long period, stretching beyond our study period (21). Thus, we may have under-estimated the impacts of healthcare disruption. It will be important to follow experiences of our cohort members over longer time periods to determine whether this is the case. Additionally, some have questioned how sensitive avoidable hospitalisations are to health system performance, as they may be affected by issues beyond the control of health systems as well (e.g., socioeconomic deprivation) (23,50). Future research should investigate other outcomes, including moving away from composite indicators, to understand the pathways through which disruption impacts individuals. The current expansion of the UK LLC to include additional longitudinal studies and a larger participant sample size may facilitate this.

The use of vaccination status as a falsification test is a strength, but cannot definitively confirm a lack of residual confounding (27,28). People who were not vaccinated may be less connected to the health system and therefore less likely to experience disruption. Future research may consider more robust indicators.

*Conclusions*

The external shock to the health system caused by the COVID-19 pandemic significantly disrupted access to healthcare and this impact is having negative impacts of hospital admissions that could be potentially preventable. As narratives on how to respond to a pandemic, continued disruption to the NHS, and how to ‘build back better’ develop, our paper highlights the need to increase healthcare investment to tackle the short- and long-term implications of the pandemic.

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The full statement, listing the names of all relevant NCS Consortium staff, can be found here:

<https://www.ucl.ac.uk/covid-19-longitudinal-health-wellbeing/convalescence-studycollaborative>.

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This project has been approved by UK LLC and its contributing data owners and information on this project and its outputs can be accessed via UK LLC’s website (Data Use Register | UK Longitudinal Linkage Collaboration; <https://ukllc.ac.uk/>) and UK LLC’s GitHub (UK Longitudinal Linkage Collaboration GitHub; <https://github.com/UKLLC>). The UK LLC has ethical approval from the Health Research Authority Research Ethics Committee to support COVID-19 research (Haydock Committee; ref: 20/NW/0446).

UK LLC is a Trusted Research Environment developed and operated by the Universities of Bristol and Edinburgh using an underlying ‘Secure eResearch Platform’ infrastructure (<https://serp.ac.uk/>) provided by Swansea University for longitudinal research. The UK LLC is an initiative of the UKRI-funded Longitudinal Health and Wellbeing National Core Study led by University College London (Grant code: MC\_PC\_20059). This work uses data accessed within UK LLC’s Trusted Research Environment (TRE), hosted by the Secure eResearch Platform (SeRP UK). We thank the SeRP UK Team at Swansea University and NHS Digital Health and Care Wales for providing the TRE’s infrastructure and support.

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• 1970 British Cohort Study (BCS70)

• English Longitudinal Study of Ageing (ELSA)

• Medical Research Council (MRC) National Survey of Health and Development (NSHD)

• Millennium Cohort Study (MCS)

• National Child Development Study (NCDS)

• Next Steps

• The UK Household Longitudinal Study (Understanding Society).

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**Data sharing**

Datasets used in the study contain sensitive and personal data, which means that data cannot be openly shared. All data can be accessed by accredited researchers through application to UK Longitudinal Linkage Collaboration (<https://ukllc.ac.uk/>). R scripts to replicate the analyses presented in the paper can be openly accessed at <https://github.com/markagreen/healthcare_disruption_LLC>.

**Author contributions**

MAG and SVS developed the idea of the study from conception. MM and JM helped to refine the research questions and study design further. MAG, with support from OH, RS and AB, accessed and manipulated the data into an analysis ready format. MAG, with support from OH, RS and SVS, conducted the analyses. MAG, MM and SVS wrote the initial draft of the manuscript, with OH, RS and JM helping to refine further. All authors approved the paper. MAG acts as guarantor for the paper.

**Ethical approval**

Ethical approval for the project was granted by the University of Liverpool’s Research Ethics Board (reference 10634).

**Transparency statement**

The lead author (Mark Green) affirms that the manuscript is an honest, accurate, and transparent account of the study being reported; that no important aspects of the study have been omitted; and that any discrepancies from the study as originally planned (and, if relevant, registered) have been explained.

**Dissemination**

Plain language summaries of the results will be shared on both the UK Longitudinal Linkage Collaboration and National Core Studies Longitudinal Health and Wellbeing websites. PPI groups run in each of these projects will input on the design and content of these summaries. A policy brief has been written and will be openly shared on the National Core Studies Longitudinal Health and Wellbeing website (as well as e-mailed to relevant policy contacts). The paper will be shared on social media via Twitter on the personal accounts of the authors. An infographic has also been created to share via social media. We will release a press release of the main findings to share the results more widely.

**Competing interests**

None declared.

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