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Evaluating the impact of a pulse oximetry remote monitoring programme on mortality and healthcare utilisation in patients with COVID-19 assessed in emergency departments in England: a retrospective matched cohort study

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Handling editor Richard Body

► Additional supplemental material is published online only. To view, please visit the journal online (http://dx.doi.org/10.1136/emermed-2022-212377).

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Received 8 February 2022
Accepted 21 December 2022
Published Online First 28 February 2023

Linked

► http://dx.doi.org/10.1136/emermed-2023-213195

Check for updates

To cite: Beaney T, Clarke J, Alboksmaty A, *et al*. *Emerg Med J* 2023;**40**:396–403.

ABSTRACT

Background To identify the impact of enrolment onto a national pulse oximetry remote monitoring programme for COVID-19 (COVID-19 Oximetry @home; CO@h) on health service use and mortality in patients attending Emergency Departments (EDs).

Methods We conducted a retrospective matched cohort study of patients enrolled onto the CO@h pathway from EDs in England. We included all patients with a positive COVID-19 test from 1 October 2020 to 3 May 2021 who attended ED from 3 days before to 10 days after the date of the test. All patients who were admitted or died on the same or following day to the first ED attendance within the time window were excluded. In the primary analysis, participants enrolled onto CO@h were matched using demographic and clinical criteria to participants who were not enrolled. Five outcome measures were examined within 28 days of first ED attendance: (1) Death from any cause; (2) Any subsequent ED attendance; (3) Any emergency hospital admission; (4) Critical care admission; and (5) Length of stay.

Results 15 621 participants were included in the primary analysis, of whom 639 were enrolled onto CO@h and 14 982 were controls. Odds of death were 52% lower in those enrolled (95% CI 7% to 75%) compared with those not enrolled onto CO@h. Odds of any ED attendance or admission were 37% (95% CI 16% to 63%) and 59% (95% CI 32% to 91%) higher, respectively, in those enrolled. Of those admitted, those enrolled had 53% (95% CI 7% to 76%) lower odds of critical care admission. There was no significant impact on length of stay.

Conclusions These findings indicate that for patients assessed in ED, pulse oximetry remote monitoring may be a clinically effective and safe model for early detection of hypoxia and escalation. However, possible selection biases might limit the generalisability to other populations.

WHAT IS ALREADY KNOWN ON THIS TOPIC

⇒ Hypoxia is known to be an important predictor of mortality and the need for hospital admission in patients with COVID-19.
⇒ The NHS COVID-19 Oximetry @home (CO@h) programme provided pulse oximeters to people with COVID-19 in the community in England, to support self-monitoring and early detection of hypoxia but the clinical effectiveness was unknown.

WHAT THIS STUDY ADDS

⇒ This study found that in patients assessed in EDs and who were not admitted within 24 hours, those enrolled in the programme had significantly lower mortality and requirement for critical care within 28 days than those not enrolled.
⇒ Patients enrolled to the programme had higher odds of subsequent ED attendance and emergency hospital admission suggesting early recognition of hypoxia and escalation of care.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY

⇒ Our findings suggest the CO@h programme is a safe pathway for patients with COVID-19, and with some evidence of a benefit on mortality, but potential selection bias in patients enrolled on the programme may limit the generalisability to other populations.

BACKGROUND

The COVID-19 pandemic has placed a huge demand on health systems around the world and led to an increase in use of digital technologies in public health responses and healthcare settings.[1–3] In the NHS in England, embracing digital technologies was a priority even before the pandemic,[4] with system pressures from COVID-19 driving an increased pace of adoption.[2] Remote monitoring devices have been highlighted as one of the technologies with the greatest potential impact on healthcare services,[4] with evidence suggesting that these can improve outcomes in selected patient groups.[5]

Early in the pandemic, it was recognised that hypoxia is a key prognostic marker and is strongly

associated with mortality from COVID-19.[6] A hallmark of COVID-19 is the relative frequency of asymptomatic ('silent') hypoxia, making measurement of oxygen saturations a critical part of clinical assessment.[7 8] In England, NHS England and Improvement launched the national COVID-19 Oximetry @ home (CO@h) programme in November 2020 to provide pulse oximeters to higher-risk people diagnosed with COVID-19 to support self-management and early recognition of hypoxia.[9] The intention of the programme, implemented in the community, was to accept referrals from primary care, NHS Test and Trace, ambulance services, and hospital EDs. In contrast, 'COVID-19 virtual wards' operated from hospitals for those discharged following admission.[10]

Initial eligibility criteria for CO@h included adults aged 65 years or over, those designated as clinically extremely vulnerable (CEV), or where clinical judgement applied, although eligibility could vary across sites.[9] Those enrolled were encouraged to record three oximetry readings daily with advice for escalation dependent on oxygen saturation, but with differences between sites in the method of recording and reporting readings, and staff contact.[9] Implementation of the national programme built on an earlier pilot in four sites in England which was found to be a safe pathway for people with COVID-19.[11]

Current evidence for the effectiveness of the programme is lacking, with two previous analyses as part of the evaluation of the CO@h programme showing no impact on mortality at a population level.[12 13] However, these studies found low overall enrolment onto the programme which may dilute any effects of the programme for those people enrolled, when using population-based designs. In this study, using a participant-level design, our aim is to identify any association of enrolment to the CO@h programme with 28-day mortality, subsequent ED presentation, hospital admission, critical care admission and hospital length of stay. To reduce the impact of possible selection bias onto the programme when using an individual-level approach, we examined outcomes in patients seen in ED who were assessed as well enough for discharge and not requiring immediate admission to hospital.

METHODS

This study used a retrospective matched cohort design. The eligible cohort included all people resident in England with a positive COVID-19 test result between 1 October 2020 and 3 May 2021, who attended an NHS ED in England within a 14-day time window from 3 days before to 10 days after the date of their positive test. For all eligible patients, an ED index date was created as the first ED attendance date within this time window. For those enrolled, the attendance date on the same day or day prior to enrolment, within the time window, was used. Patients who were admitted to hospital or died on the same or following day to their index ED attendance (ie, were too unwell to be considered for the programme) were excluded. Patients admitted to hospital in the 14 days before their index ED attendance were also excluded, as were care home residents, as different monitoring pathways may have operated for these groups.[14] We compared patients enrolled onto the CO@h programme on the same or following day to their index ED attendance ('treated') with those not enrolled ('controls'). Five outcomes were assessed, measured up to 28 days from index ED attendance:

1. Death from any cause.
2. One or more ED attendances.
3. One or more emergency hospital admissions.
4. One or more critical care admissions (of those admitted to hospital).
5. Total hospital length of stay in days, of those admitted who did not die within 28 days.

Data sources and processing

Data on patients enrolled to the CO@h programme were submitted from participating sites via NHS Digital's Strategic Data Collection Service.[15] Data on people with a positive COVID-19 test were obtained from the Public Health England Second Generation Surveillance System,[16] which collates positive results from laboratories across England.[17] The date of a first positive COVID-19 test was taken for each individual in cases where more than one test was recorded. ED attendance data were provided through the Emergency Care Data Set.[18] Hospital admission data were provided from Hospital Episode Statistics (HES), linked to death registration data from the Office for National Statistics.[19] In patients admitted, total length of stay was capped at 28 days where a patient was discharged after the 28-day window. Patient demographics and chronic conditions were sourced from primary care data through the General Practice Extraction Service Data for Pandemic Planning and Research (GDPPR).[20] Data were linked using a deidentified NHS patient ID.

Demographic data, including age, sex, ethnicity and lower layer super output area (LSOA) of residence were derived from GDPPR, or, if missing, from HES or ECDS. Deciles of the Index of Multiple Deprivation (IMD) 2019 were linked to LSOA of residence.[21] Data on CEV status (see online supplemental appendix box A1),[22] body mass index (BMI), smoking and chronic conditions were derived from GDPPR. The following chronic conditions were included: hypertension, chronic cardiac disease, chronic kidney disease, chronic respiratory disease, dementia, diabetes, chronic neurological disease (including epilepsy), learning disability, malignancy/immunosuppression, severe mental illness, peripheral vascular disease and stroke/transient ischaemic attack. In each case, the latest codes were selected prior to the date of the positive COVID-19 test, to exclude those potentially resulting from COVID-19 infection. For the variables age, sex and ethnicity only, if no data were recorded prior to the date of the COVID-19 test, the earliest data following the COVID-19 test was used. In cases where the latest Systematised Nomenclature of Medicine Clinical Terms (SNOMED-CT) code indicated resolution of a condition, the condition was excluded. Further details of the data sets and processing are given in online supplemental appendix.

Statistical methods

Univariable logistic regression was used to estimate the odds ratio (OR) for each of the four binary outcomes in those enrolled compared with controls and negative binomial regression was used to estimate the treatment effect of the programme on length of stay. Analyses of length of stay excluded patients who died during admission within the 28-day time window.

In the primary analysis, to account for potential differences in patient characteristics between groups, those enrolled to CO@h were matched to those not enrolled based on the following variables: age category, sex, ethnicity, terciles of IMD score, BMI category, month of ED index date, CEV status and days from COVID-19 test to ED index date (categorised as −3 to −1 days, 0–4 days, 5–10 days). The variables for inclusion in the model were chosen *a priori*. Patients with missing values for any of the matching covariates were excluded from analysis.

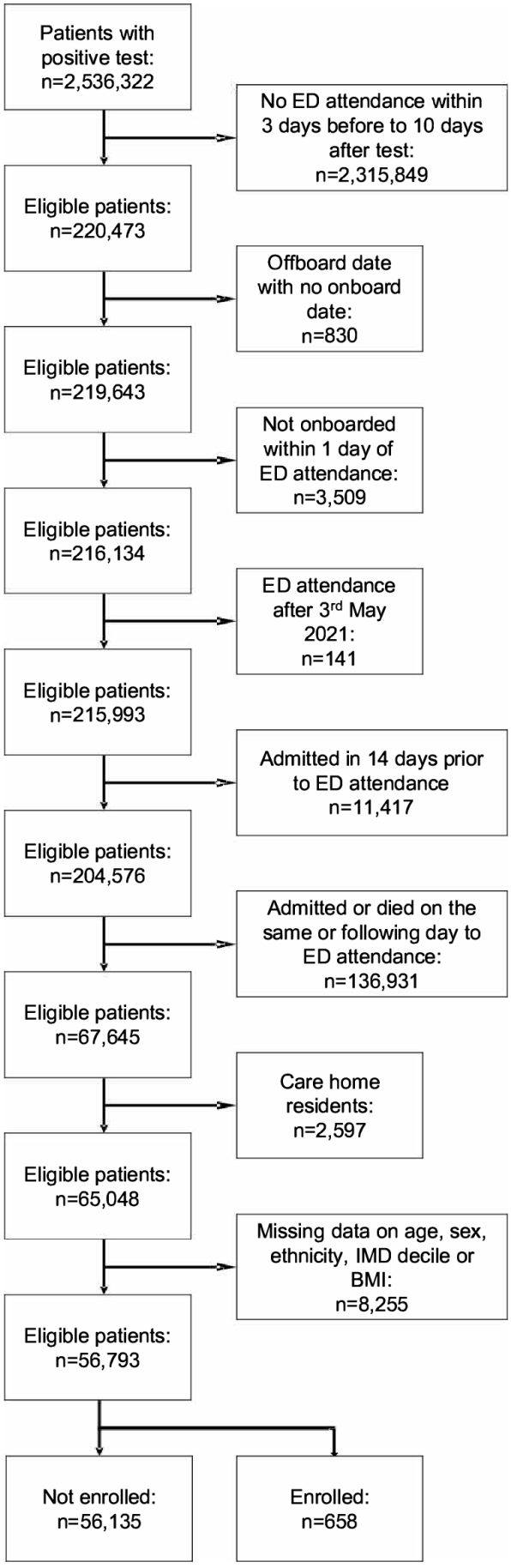

Figure 1 Flow chart for eligibility criteria for cohort

The characteristics of patients who could not be matched by the algorithm (because no control was available) were described and differences compared using χ^2 tests. After matching, regression models were run including stratum-specific weights from the matching algorithm to account for unequal stratum sizes. Enrolled patients who were unmatched were excluded from the matched analysis. A subgroup analysis was performed for patients aged 50 years or more, using the matched model.

A series of sensitivity analyses were carried out for the primary analysis to assess the sensitivity of inferences to changes in the model assumptions. The first compared the impact of changing the exclusion timeframe between ED attendance and admission/death from 1 day to (1) The same day only or (2) Within 2 days. The second sensitivity analysis assessed potential differences in COVID-19 outcomes between the enrolled versus control groups, for two outcomes:

1. Twenty-eight days mortality using only deaths where COVID-19 was listed as the primary cause of death.
2. Twenty-eight days emergency hospital admissions where COVID-19 was listed as a primary or secondary diagnosis.

Two additional sensitivity analyses were applied for each outcome to assess the robustness of inferences to the matching algorithm. These models included additional patient risk factors, in addition to two markers of prior healthcare utilisation to account for possible differences in health-seeking behaviours between the two groups:

1. A doubly robust model, adjusted for the same covariates included in the matching, plus: smoking status, 12 chronic diseases and the number of A&E attendances and emergency hospital admissions in the year up until 2 weeks before the positive COVID-19 test. In adjusted models, deciles of IMD Score were used rather than the terciles used in matching.
2. A covariate-adjusted model, adjusted for the same variables as the doubly robust model, but without use of matching. This model included all enrolled patients, including those that were not matched in the primary analysis.

Further details are given in the online supplemental appendix.

Analyses were conducted in the Big Data and Analytics Unit Secure Environment, Imperial College. Python V.3.9.5 and Pandas V.1.2.3 were used in data manipulation. Matching was conducted in Stata V.17.0, using the Coarsened Exact Matching (*cem*) command.[23]

Patient and public involvement

Patients or the public were not involved in the design, conduct or reporting of our research.

RESULTS

Between 1 October 2020 and 3 May 2021, 2536 322 patients were identified with a positive COVID-19 test. Of these, 220 473 (8.7%) attended ED from 3 days before to 10 days after the positive test. After applying the exclusion criteria, 65 048 patients remained in the analysis, of whom 743 (1.1%) were enrolled to CO@h, and 64 305 (98.9%) were not enrolled (figure 1). There were significant differences in the characteristics of patients enrolled versus those not enrolled to CO@h (table 1) . Patients enrolled were more likely to be aged 50–79 years than those not enrolled, and more likely to be of white ethnicity, living in areas of higher socioeconomic deprivation and to be obese.

Of the eligible cohort, 11 (1.5%) of those enrolled died within 28 days, compared to 1,768 (2.7%) of those not enrolled (table 2). In an unadjusted analysis, the odds of 28-day mortality were 47% lower in those enrolled to CO@h (95% CI 0.29 to

Table 1 Characteristics of the eligible study population, stratified by enrolment to the CO@h programme

	Not enrolled		Enrolled		
	Number	Percentage	Number	Percentage	P value*
Age category (years)					
18–49	36 037	56.0%	328	44.1%	<0.001
50–64	17 871	27.8%	279	37.6%	
65–79	7267	11.3%	107	14.4%	
80 or more	3130	4.9%	29	3.9%	
Sex					
Female	34 282	53.3%	378	50.9%	<0.001
Male	27 644	43.0%	365	49.1%	
Missing	2379	3.7%	0	0.0%	
Ethnicity					
Asian/Asian British	11 543	18.0%	116	15.6%	0.002
Black/African/Caribbean/Black British	3710	5.8%	20	2.7%	
Mixed/multiple ethnic groups	1428	2.2%	11	1.5%	
Other ethnic group	2791	4.3%	29	3.9%	
White	41 797	65.0%	535	72.0%	
Missing	77	0.1%	1	0.1%	
IMD tertile					
1 (most deprived)	28 695	44.6%	379	51.0%	0.002
2	20 471	31.8%	227	30.6%	
3 (least deprived)	15 062	23.4%	136	18.3%	
Missing	77		1		
Body mass index					
Underweight	1281	2.0%	†	†	<0.001†
Healthy weight	14 461	22.5%	115†	15.5%†	
Overweight	18 902	29.4%	230†	31.0%†	
Obese	21 920	34.1%	320†	43.1%†	
Missing	7741	12.0%	80†	10.8%†	
CEV					
Not CEV	54 832	85.3%	627	84.4%	0.501
CEV	9473	14.7%	116	15.6%	
Smoking status					
Never smoker	37 445	58.2%	410	55.2%	0.015
Ex-smoker	14 295	22.2%	200	26.9%	
Current smoker	9431	14.7%	105	14.1%	
Missing	3134	4.9%	28	3.8%	
Comorbidities					
Hypertension	12 958	20.2%	181	24.4%	0.004
Chronic cardiac disease	5269	8.2%	67	9.0%	0.416
Chronic kidney disease	640	1.0%	†	†	>0.5†
Chronic respiratory disease	17 557	27.3%	257	34.6%	<0.001
Dementia	554	0.9%	†	†	0.05–0.5†
Diabetes	8955	13.9%	127	17.1%	0.013
Chronic neurological disease (including epilepsy)	2739	4.3%	35	4.7%	0.545
Learning disability	462	0.7%	†	†	>0.5†
Malignancy or immunosuppression	6448	10.0%	73	9.8%	0.855
Severe mental illness	2122	3.3%	19	2.6%	0.259
Peripheral vascular disease	555	0.9%	10	1.3%	0.158
Stroke or TIA	1772	2.8%	23	3.1%	0.574
Month of COVID-19 test					
September/October	6673	10.4%	†	†	<0.001†
November	8877	13.8%	†	†	
December	14 584	22.7%	30†	4.0%†	
January	23 211	36.1%	405†	54.5%†	
February	6944	10.8%	200†	26.9%†	
March	2731	4.2%	75†	10.1%†	
April/May	1285	2.0%	20†	2.7%†	
Days from ED attendance to COVID-19 test					

Continued

Table 1 Continued

	Not enrolled		Enrolled		
	Number	Percentage	Number	Percentage	P value*
–3 to –1 days	11 504	17.9%	35	4.7%	<0.001
0–4 days	29 003	45.1%	354	47.6%	
5–10 days	19 311	30.0%	300	40.4%	
Total	64 305		743		

*P value from χ^2 test comparing proportions not enrolled to enrolled.
†Small values for non-missing data suppressed, and remaining values for variable rounded to nearest 5; values of p reported as, <0.001, <0.05, 0.05–0.5, or>0.5.
CEV, clinically extremely vulnerable; CO@h, COVID-19 Oximetry @home; IMD, Index of Multiple Deprivation; TIA, transient ischaemic attack.

0.97; p=0.04) compared with those not enrolled (table 2). Among those enrolled, odds of a subsequent ED attendance were 29% higher (95% CI 1.10 to 1.51; p=0.002) and odds of emergency hospital admission were 59% higher (95% CI 1.34 to 1.89; p<0.001). There was weak evidence of lower critical care admissions of those enrolled (95% CI 0.30 to 1.04; p=0.065) and no evidence of a difference in hospital length of stay (p=0.221).

Matched analysis

Of the 56 793 patients with complete data on sex, ethnicity, IMD and BMI, 658 (1.2%) were enrolled and 56 135 (98.8%) were not enrolled. Of the enrolled patients 639 (97.1%) were matched to 14 982 controls (representing 26.7% of total controls) giving a total of 15 621 in the primary analysis. The characteristics across each of the matching variables of the 19 unmatched and the 639 matched enrolled patients are given in the online supplemental appendix table A1. Those unmatched were more likely to be older, of non-white ethnic background, overweight and identified as CEV, although total numbers were small. There were no significant differences in the outcomes for the enrolled matched compared with unmatched patients.

After matching, patients enrolled had significantly lower odds of 28-day mortality (OR 0.48, 95% CI 0.25 to 0.93; p=0.030) compared with those not enrolled (table 3). In contrast, those enrolled had a significant increase in the odds of any ED attendance or hospital admission (OR 1.37, p<0.001 and OR 1.59, p<0.001, respectively). Among those admitted to hospital, patients previously enrolled had 0.47 times the odds of receiving critical care (95% CI 0.24 to 0.93, p=0.030). Of admitted patients, there was no significant difference in total length of stay from negative binomial regression models. A subgroup analysis of patients aged 50 years or more demonstrated similar estimates to the whole cohort (online supplemental appendix table A2).

Sensitivity analyses

A sensitivity analysis altering the exclusion criteria for the timeframe from ED attendance to death or admission and a second using only deaths directly caused by COVID-19 or admissions where COVID-19 was listed as a diagnosis produced similar inferences to the primary model (online supplemental appendix tables A3-A5). However, the model excluding deaths and admissions only on the same day as ED attendance (instead of within 1 day as in the primary model) resulted in a lower odds of hospital admission in those enrolled due to exclusion of a relatively larger number of people with a same-day admission in the control group compared with the enrolled group (online supplemental appendix table A3).

A doubly robust model adjusted for all matching variables, in addition to presence of chronic conditions, smoking status, and the number of ED attendances and emergency hospital admissions in the previous year. The distributions of the adjusting covariates were similar in the enrolled and control groups for the unmatched variables (online supplemental appendix table A6). Effect sizes for the conditional ORs were slightly larger in magnitude compared with the primary matched model, but these changes did not affect the inferences (table 4). A second sensitivity analysis with a covariate adjusted model, without matching, also found similar conditional effects sizes to the primary matched model (online supplemental appendix table A7).

DISCUSSION

In a retrospective matched cohort study of patients with a positive COVID-19 test assessed in ED, those enrolled onto the CO@h programme were found to have 52% lower odds of mortality and (of those admitted to hospital) 53% lower odds of critical care use within 28 days compared with those who were not on the programme. In contrast, enrolment was associated with a 37% increase in the odds of any subsequent ED attendance and a

Table 2 Outcomes in those enrolled to CO@h versus not enrolled, and ORs for enrolment

	Not enrolled		Enrolled					95% CI		
Outcome	Number	Percentage	Number	Percentage	OR	SE	P value	Lower	Upper	Denominator
Death within 28 days	1768	2.7%	11	1.5%	0.53	0.16	0.04	0.29	0.97	65 048
Any ED attendance within 28 days	15 463	24.0%	215	28.9%	1.29	0.10	0.002	1.10	1.51	65 048
Any hospital admission within 28 days	10 051	15.6%	169	22.7%	1.59	0.14	<0.001	1.34	1.89	65 048
Any critical care use of those admitted	1109	11.0%	11	6.5%	0.56	0.18	0.065	0.30	1.04	10 220
	Mean	SD	Mean	SD	IRR	SE	P value	Lower	Upper	Denominator
Length of stay (days)	6.70	6.40	6.15	5.54	0.904	0.075	0.221	0.768	1.063	9237

CO@h, COVID-19 Oximetry @home; IRR, incidence rate ratio; OR, odds ratio; SD, standard deviation; SE, standard error.

Table 3 Effect estimates associated with enrolment to CO@h for each study outcome after matching

Outcome	OR	SE	P value	95% CI Lower	95% CI Upper	Denominator
Death within 28 days	0.48	0.16	0.030	0.25	0.93	15621
Any ED attendance within 28 days	1.37	0.12	<0.001	1.16	1.63	15621
Any hospital admission within 28 days	1.59	0.15	<0.001	1.32	1.91	15621
Any critical care use of those admitted	0.47	0.16	0.030	0.24	0.93	2272
	IRR	**SE**	**P value**	**Lower**	**Upper**	**Denominator**
Length of stay (LOS) of those admitted	0.931	0.077	0.384	0.791	1.094	2135

CO@h, COVID-19 Oximetry @home; IRR, incidence rate ratio; OR, odds ratio; SE, standard error.

59% increase in the odds of any emergency admission within 28 days. The CO@h programme intends to enable early detection of hypoxia, and more timely clinical assessment and hospital admission. It was expected that this might reduce mortality and the need for critical care admission through prompt oxygen therapy, and access to medical treatments shown to reduce mortality and the need for mechanical ventilation.[24–26] Our findings provide some evidence for this, although total numbers were small, with wide confidence intervals for the estimates. The expectation of whether home monitoring would increase or decrease ED attendances and hospitalisations was less clear, and our findings of an increase in both highlight that the programme should not be viewed as a pathway to prevent hospital attendance, but rather as a pathway to support appropriate escalation and decision-making for assessment or admission.

In a separate study of the CO@h programme by the same authors, analysing clinical outcomes across the whole population of people eligible for the programme in England, there was no effect on mortality and small increases in ED attendances and hospital admissions following implementation.[12] This study found only 2.5% of eligible people nationally were enrolled, which, although likely to be an underestimate of true enrolment, will dilute the effect of the programme at a population level. Taken together, these findings suggest that while the CO@h programme may promote timely detection of deterioration and escalation of care in those enrolled, the programme could not be provided at a wide enough scale to benefit the whole population as anticipated.

There is limited pre-existing evidence for the effectiveness of pulse oximetry in health outcomes in patients with COVID-19.[27] A previous evaluation of the COVID-19 pulse oximetry pilot programme in four sites in England found that none of those under 65 years and without long-term conditions died during the study, suggesting there were no safety concerns in lower-risk patients, but without a control group to compare differences in clinical outcomes.[11] A recent systematic review identified 13 studies of pulse oximetry monitoring in COVID-19, but only 2 studies included control groups and only 1 of these compared health outcomes.[28] Gordon *et al* (2020) found lower odds of ED presentation or re-admission in patients discharged from hospital with remote monitoring, compared with those not enrolled.[29] However, the population discharged from hospital, analogous to the 'virtual wards' programme in England, is likely to be a very different patient group to those considered for community enrolment through the CO@h programme. A study of a telemonitoring service in Spain that reported lower hospitalisations and mortality in those enrolled compared with the regional population, however, did not adjust for case mix in the control population.[30]

Further research is needed to identify other potential benefits and risks of the programme beyond clinical effectiveness and safety, including user experience of both patients and healthcare staff and the cost-effectiveness of the programme. There is also a need to understand equity of the programme, both in terms of access to the programme and whether outcomes vary between different groups of people, which may allow for more effective targeting of the service.

Strengths and limitations

A strength of this study is the use of data on those enrolled to the CO@h programme, as well as comprehensive data on all people resident in England with a positive COVID-19 test, allowing matching of people enrolled to controls who would have been

Table 4 Effect estimates associated with enrolment to CO@h for each study outcome, after matching and adjusted for smoking, comorbidities and prior healthcare utilisation

Outcome	Adjusted OR	SE	P value	95% CI Lower	95% CI Upper	Denominator
Death within 28 days	0.42	0.16	0.022	0.20	0.88	15327†
Any ED attendance within 28 days	1.43	0.13	<0.001	1.20	1.71	15621
Any hospital admission within 28 days	1.68	0.17	<0.001	1.38	2.04	15621
Any level 2/3 care of those admitted	0.43	0.15	0.019	0.21	0.87	2,249*
	Adjusted IRR	**SE**	**P value**	**Lower**	**Upper**	**Denominator**
Length of stay (days) of those admitted	0.996	0.078	0.963	0.85	1.16	2135

*No critical care use of those admitted in April/May or mixed/multiple ethnic groups or underweight group.
†No deaths in November/April/May or mixed/multiple ethnic groups.
CO@h, COVID-19 Oximetry @home; IRR, incidence rate ratio; OR, odds ratio; SE, standard error.

eligible for the programme but were not enrolled. Use of linked primary and secondary care data allowed the analysis to match using underlying patient risk factors, as well as month of test, to account for variation in outcomes over time[31] and days from test to ED attendance, to account for differences in the course of disease over time. However, date of symptom onset was not available, so we were unable to account for confounding by time from symptoms to test. Matching criteria were determined *a priori* and use of different matching variables might impact the findings. However, in the unmatched analysis (table 2) and two sensitivity analyses with different model specifications (table 4 and online supplemental appendix table A7), inferences were robust. Despite this, the total number of deaths and critical care admissions for the enrolled group were small (11 for both) which may increase the risk of a type 1 error.

Measures of healthcare utilisation in this study may be affected by death as a competing risk for hospital attendance. Patients who died could not later be admitted, and given deaths were lower in the enrolled than the unenrolled group, lower mortality in those enrolled could allow for higher observed healthcare use. However, we expect the impact of this to be small, given that the number of deaths were small compared with the number of ED attendances and admissions. Furthermore, from a health service perspective, increases in healthcare use are of interest, irrespective of whether these are causally related to home pulse oximetry or are due to fewer deaths in those enrolled.

It is likely that there remains some residual confounding by disease severity and clinical acuity, for which participants could not be matched. Decisions by clinicians in ED on whether to admit or enrol patients will be influenced by disease severity at the time of presentation, and if there were systematic differences in severity in those enrolled compared with those not enrolled, the findings of our study will be biased. However, we believe there are two arguments that indicate it is unlikely that those enrolled had less severe disease than those not enrolled, and if anything, those enrolled are more likely to have had more severe disease. First, if those enrolled had systematically lower severity, in the absence of any programme effect, we would expect admissions and mortality to reduce in parallel, rather than the divergent pattern (higher odds of admission but lower odds of mortality) seen in the results. Second, in the context of clinical assessment in ED of whether to admit a patient, reassurance provided by a remote monitoring pathway may lower the threshold for ED discharge, leading to the inclusion of a higher severity group in those enrolled.

Additional biases in patient selection may impact on the similarity of the two groups, such as through selection of those with greater digital literacy or exclusion of those who were already monitoring their oxygen saturations using personally purchased oximeters. It is possible that health-seeking behaviours varied between groups, and if those enrolled had a lower threshold for presenting to services, this may partly explain the patterns seen. The doubly robust sensitivity analysis adjusted for ED presentations and hospitalisations in the year prior to testing positive for COVID-19 and was consistent with the primary analysis which provides some reassurance that the impact of selection bias here is small. Outcome metrics were also based on all-cause mortality or admissions within 28 days, which may lead to bias if one group had a larger contribution from causes unrelated to COVID-19. However, a sensitivity analysis of deaths or admissions attributable to COVID-19 (online supplemental appendix table A3), indicated the results to be robust.

The findings of this study apply to the subset of people with COVID-19 who were reviewed in ED but did not require immediate admission, and who did not die within 1 day of ED attendance. As a result, the findings may not be generalisable to the wider population eligible for the programme, for example, those referred in from primary care, or those presenting at an earlier or later stage of disease. Only 1.2% of the eligible cohort were enrolled, but this should not be viewed as the true enrolment of patients presenting to ED with COVID-19, due to the strict criteria for selection used in this study. The outcome estimates also exclude those with the most severe disease, who were admitted or died within 24 hours of ED attendance and so may not be comparable to estimates from other studies.

The CO@h programme is not a homogenous programme, with variation in the type of model implemented, and it is unlikely that a single effect estimate will be representative across all sites.[14] Clinical decision-making with regards to enrolment will also be specific to both ED and CO@h site, particularly given the emphasis on clinical judgement to determine eligibility.[9] Given the small number of enrolled patients in our study, data were insufficient to match on ED location, or to examine outcome measures within single sites. There may also be groups of patients for whom the programme is more suitable, and concern that pulse oximetry is more likely to be falsely reassuring in people with black or brown skin;[8] however, due to the small sample size, subgroup analyses were outside the scope of the studytable 1.

CONCLUSION

The CO@h programme, implemented in England from November 2020, sought to enable early recognition and intervention for people with COVID-19-induced hypoxia. Among people assessed and discharged from ED, this study found lower odds of mortality and critical care admission and higher odds of subsequent ED attendance and emergency hospital admission in those enrolled compared with those not enrolled to the programme. These findings indicate that for individual patients, pulse oximetry remote monitoring may be an effective pathway to support early detection of hypoxia and escalation of care in patients with COVID-19.

Correction notice Since this paper was published online it has been updated. Table citations have been reordered and updated.

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Acknowledgements The authors thank Hutan Ashrafian, Gianluca Fontana, Saira Ghafur, Melanie Leis and Mahsa Mazidi for their input and support. The authors also thank the Big Data and Analytical Unit (BDAU) at the Institute of Global Health Innovation (IGHI), Imperial College London for providing data management. The authors also thank the other evaluation teams collaborating on the CO@h programme: the National Institute for Health Research (NIHR) BRACE and RSET team, the Nuffield Trust and the Improvement Analytics Unit, a partnership between The Health Foundation and NHS England.

Contributors All authors were involved in the conceptualisation of the study, interpretation of the findings and in the reviewing and editing of the manuscript. TB, JC, KF, JB, PA, SE, AD and ALN developed the study design and methodology. TB and JC conducted the data management and formal analysis, supported by ALN. TB wrote the first draft of the manuscript. TB is the guarantor and accepts full responsibility for the work and the conduct of the study, had access to the data, and controlled the decision to publish.

Funding This work was funded by NHS England (award number: P012627) and supported by the NIHR Imperial Patient Safety Translation Research Centre (award number not applicable). Infrastructure support was provided by the NIHR Imperial Biomedical Research Centre (BRC). TB received support from the NIHR Applied Research Collaboration Northwest London. JC was supported by the Wellcome Trust (215938/Z/19/Z).

Disclaimer The study funders did not play a role in study design; in the collection, analysis, and interpretation of data; in the writing of the report; and in the decision to submit the article for publication. In addition, researchers were independent from

funders, and all authors had full access to all of the data included in this study and can take responsibility for the integrity of the data and the accuracy of the data analysis.

Competing interests All authors have completed the ICMJE uniform disclosure form at http://www.icmje.org/disclosure-of-interest/ and declare: JC has received fees from Philips UK Limited for consultancy services outside of the submitted work. SE has received fees for an educational lecture sponsored by Astra Zeneca and is co-clinical director for the NHS England and Improvement London Respiratory Network. All other authors report no support from any organisation for the submitted work; no financial relationships with any organisations that might have an interest in the submitted work in the previous three years; no other relationships or activities that could appear to have influenced the submitted work.

Patient and public involvement Patients and/or the public were not involved in the design, or conduct, or reporting, or dissemination plans of this research.

Patient consent for publication Not applicable.

Provenance and peer review Not commissioned; externally peer reviewed.

Data availability statement Data may be obtained from a third party and are not publicly available. The patient level data used in this study are not publicly available but are available to applicants meeting certain criteria through application of a Data Access Request Service (DARS) and approval from the Independent Group Advising on the Release of Data.

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Appendix A

Evaluating the impact of a pulse oximetry remote monitoring programme on mortality and healthcare utilisation in patients with COVID-19 assessed in Emergency Departments in England: a retrospective matched cohort study

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Entry criteria for COVID Oximetry @home

Eligibility for the COVID Oximetry @home (CO@h) programme is defined in the NHS England Standard Operating Procedure (SOP) although there was flexibility is operational models and eligibility across sites.[1]

Monitoring requirements could vary across sites, and involve text messages, email prompts or check-in calls, or support for full self-management and escalation.[1] Pulse oximeters were purchased by individual sites, or requested from the NHS Supply Chain and were required to meet ISO 80601-2-61:2017 and be CE marked.[1]

Data cleaning

Note: the described datasets were used for several distinct analyses by the study team, with data cleaning rules the same or similar between studies. For this reason, some of the text in the appendices may be identical to that of other published articles by the study authors on the same data source.

COVID-19 testing data

Testing data was provided through the Public Health England Second Generation Surveillance System (SGSS). This dataset captures routine laboratory data on infectious diseases for England, including COVID-19, with all diagnostic laboratories required to notify positive test results within 24 hours.[2] Data included 3,251,225 tests performed from 1st October 2020 to 30th June 2021, inclusive.

Provided data included test date and result date. 99% of results were reported within 5 days of the test, and 6,544 (0.2%) were reported more than 7 days from date of test. Where the result data occurred before the test date. In 1,603 cases, the result date was recorded as prior to the test date. In these instances, where the difference between the testing date and reporting date was 7 days or less, the test date and reporting date were swapped. In the 191 instances where reporting date was more than 7 days before the testing date, the test was excluded.

For this analysis, only tests performed up to 3rd May 2021 were included (after swapping test and result dates where applicable), given that secondary care data was available up until the end of May 2021. Of the 2,928,802 positive COVID-19 tests, 2,352,390 (80.3%) were from Pillar 2 testing, 561,852 (19.2%) from Pillar 1, and 14,560 (0.5%) from Pillar 4.[3] Test type was recorded for Pillar 2 tests only, and of these, 2,250,288 (95.7%) were Polymerase Chain Reaction (PCR) tests, 102,102 (4.3%) were lateral flow tests.

For this analysis, only the first positive test was taken where more than one was recorded for any given individual, resulting in a total eligible population of 2,536,322.

COVID Oximetry @home (CO@h) programme data

Data on patients enrolled ('onboarded') onto the CO@h programme were submitted directly from CO@h sites via NHS Digital's Strategic Data Collection Service.[4] Data included a deidentified NHS patient ID of the patient onboarded, along with the date of onboarding to and offboarding from the programme. Any patient with an offboarding date but no onboarding date were excluded from the analyses.

Shielded Patient List

Identification of high-risk patients, designated 'Clinically Extremely Vulnerable' (CEV) was provided via a linkage from the NHS Digital Shielded Patient List (SPL) to the primary care record.[5] Patients with any of the conditions listed in Box A1 below were designated as high risk.[6] Code lists for the conditions are available to download from NHS Digital.[7] In addition, from February 2021, people were also added to the list if identified as high risk using the QCovid risk prediction model, which combines factors including age, sex, ethnicity, BMI as well as specific conditions.[8] Thresholds of mortality risk for inclusion in the SPL were an absolute risk of 0.5% or higher, or a relative risk of 10 times the baseline risk of a person with the same age and sex.[6] GP practices and NHS Trusts were also able to add and remove patients from the SPL based on clinical judgment and individual risk assessments.[9]

Box A1: NHS Digital criteria for Clinically Extremely Vulnerable patients:

- solid organ transplant recipients
- people with severe respiratory conditions including all cystic fibrosis, severe asthma and severe chronic obstructive pulmonary (COPD)
- people with rare diseases and inborn errors of metabolism that significantly increase the risk of infections (such as Severe combined immunodeficiency (SCID), homozygous sickle cell)
- people on immunosuppression therapies sufficient to significantly increase risk of infection
- people who have problems with their spleen, for example have had a splenectomy
- adults with Down's syndrome
- adults on dialysis with kidney impairment (Stage 5 Chronic Kidney Disease)
- women who are pregnant with significant heart disease, congenital or acquired
- people with cancer who are undergoing active chemotherapy
- people with lung cancer who are undergoing radical radiotherapy
- people with cancers of the blood or bone marrow such as leukaemia, lymphoma or myeloma who are at any stage of treatment
- people having immunotherapy or other continuing antibody treatments for cancer
- people having other targeted cancer treatments which can affect the immune system, such as protein kinase inhibitors or PARP inhibitors
- people who have had bone marrow or stem cell transplants in the last 6 months, or who are still taking immunosuppression drugs

Source: https://digital.nhs.uk/coronavirus/shielded-patient-list/risk-criteria

Primary care data

Primary care data came from the General Practice Extraction Service (GPES) Data for Pandemic Planning and Research (GDPPR).[10] Data included month and year of birth, sex, ethnicity, Lower Layer Super Output Area (LSOA) of residence, a marker for Clinically Extremely Vulnerable (CEV) status, and a marker for residence in a care home. LSOA was used to link to 2019 deciles of Index of Multiple Deprivation (IMD).[11] Age was calculated from date of positive COVID-19 test, assuming a birthdate on the 15th day of the month.

Entries include a date to which each journal item applies, and a date on which the journal item was recorded. The former was used in priority, but where missing, was replaced with the journal item recording date. For LSOA, CEV status and care home residence, only entries occurring up to the date of positive COVID-19 test were included. For month and year of birth, sex and ethnicity, if no entry were included prior to the date of COVID-19 test, then the earliest recorded entry after the test was included.

Secondary care data

Data on hospital admissions came from the Hospital Episode Statistics (HES) data set up to 31st May 2021, linked to Office for National Statistics (ONS) data on death registrations up to 5th July 2021.[12] Entries were excluded where missing admission dates, provider Trust code, or patient deidentified ID.

Where multiple admission episodes were recorded within a spell, a single spell start and end date were created. Non-emergency hospital admissions were excluded from analyses. A binary indicator was created for any admission within 28 days of positive COVID-19 test. A second indicator was created for death (of any cause) within 28 days of positive COVID-19 test. Critical care admissions were defined as an admission episode for any level 2 or level 3 care within the defined spell.

Data on accident and emergency (A&E) attendances came from the Emergency Care Data Set (ECDS).[13] Only A&E presentations to NHS providers were selected (Trust codes beginning with 'R'). The A&E attendance date, departure date and admission date (if subsequently admitted) are included. In cases where attendance date was recorded as being

after the departure date, the attendance date was set to the departure date, if departure date was equal to the admission date. Otherwise, attendance date was assumed to be correct. Where multiple A&E attendances were recorded on the same day, a single attendance was kept for each patient, prioritising in turn:

1. Any attendance associated with an admission
2. Earliest time of attendance
3. Earliest time of departure

A binary indicator was created for one or more A&E attendances within 28 days of a positive COVID-19 test.

Where age was missing from GDPPR, it was derived from month and year of birth in HES, or if also missing in HES, derived from month and year of birth in ECDS, using the same approach as for GDPPR. Where LSOA was missing from GDPPR, it was derived from HES/ECDS. CCG was derived first from testing data, and if missing, from CO@h programme data, followed by GDPPR/HES/ECDS if missing.

Co-morbidities

SNOMED codes were included in the GDPPR dataset pertaining to specific SNOMED code cluster reference sets provided by NHS Digital.[10] 6,485 unique codes were identified from GDPPR. Codes were reviewed manually by authors TB and JC and removed if not relevant or assigned to the minimal number of relevant code clusters.

SNOMED reference clusters were aggregated into hierarchies of similar conditions. Codes in each higher-order cluster were then reviewed to ensure groupings of relevant codes and twelve relevant chronic disease categories were selected: hypertension, chronic cardiac disease, chronic kidney disease, chronic respiratory disease, dementia, diabetes, chronic neurological disease (including epilepsy), learning disability, malignancy/immunosuppression, severe mental illness, peripheral vascular disease and stroke/transient ischaemic attack (TIA). Categories for chronic respiratory disease, diabetes, epilepsy, malignancy/immunosuppression and severe mental illness included relevant medication codes. Broad diagnostic categories of diagnoses were chosen, as certain

medications were not diagnostic of more granular diagnostic categories (for example, use of a long-acting bronchodilator/inhaled corticosteroid in both COPD and asthma).

For each patient in GDPPR, all relevant diagnostic codes prior to the study index date (date of positive COVID-19 test) were considered diagnostic. In cases where the latest SNOMED code indicated resolution of a condition (e.g. 'Atrial fibrillation resolved (finding)'), then the diagnosis was excluded for that patient. SNOMED codes relating to drug codes were only included up to 2 years prior to the index date.

A full list of codes within each diagnostic category are available in our GitHub repository: https://github.com/tbeaney/Imperial-COh-evaluation

BMI categorisation

SNOMED codes for BMI were either diagnostic categories (eg 'Body mass index 30+ - obesity (finding)' or value codes (e.g. 'Body mass index (observable entity)'). Values were extracted and BMI was categorised according to the standard World Health Organisation classification of underweight (<18.5 kg/m^2), healthy weight (18.5-24.9 kg/m^2), overweight (25.0-29.9 kg/m^2) and obese (≥30.0 kg/m^2). Value codes outside of the range 5.0-100.0 kg/m2 were excluded. SNOMED codes which spanned more than one category (e.g. 'Increased body mass index (finding)') and child BMI categories were also excluded.

Smoking categorisation

Smoking status was categorised into 'never-smoker', 'ex-smoker' and 'current smoker' according to the latest SNOMED code prior to and including the index date. For any patient where the latest SNOMED code indicated 'never-smoker', but a prior record indicated active smoking, then the patient was re-categorised as 'ex-smoker.

Statistical analysis

For the matched analysis, enrolled patients ('treated') were matched with patients who were not enrolled ('controls'), using the *cem* command in Stata following the approach defined by Blackwell et al (2010).[14] Patients with any of the matching variables missing (8,255; 12.7%) were dropped for the analysis, resulting in a total of 56,135 controls and 658 treated.

The following variables were chosen *a priori* for inclusion in the matching algorithm:

- Age category (<50, 50-64, 65-79, 80+ years)
- Sex (female or male)
- Ethnicity (using the five ONS categories: White, Asian/Asian British, Black/African/Caribbean/Black British, Mixed/Multiple ethnic groups, Other ethnic groups)
- Terciles of IMD score
- BMI category (underweight, healthy weight, overweight, obese)
- Month of ED index date (September-October 2020 & April-May 2021 were combined due to small numbers in September and May)
- Clinically Extremely Vulnerable (CEV) status (yes/no)
- Days from COVID-19 test to A&E index date (cuts applied at: -3 to -1; 0 to 4; 5 to 10 days)

Logistic regression was used to estimate the treatment effect of the programme separately for each of the four binary outcomes occurring in the time period from A&E index date to 28 days:

- Death from any cause
- Any ED attendance (excluding the ED index attendance)
- Any emergency hospital admission
- Any critical care (level 2 or level 3) admission, of those admitted

Negative binomial regression was used to estimate the treatment effect of the programme on length of stay in days, for those admitted within 28 days. Total length of stay was capped at 28 days where a patient was discharged after the 28-day window, and analyses of length of stay excluded patients who died within the 28-day time window. The overdispersion parameter was calculated and the distribution of length of stay was found to be overdispersed

compared to a Poisson process in all models, indicating superior model fit for the negative binomial model compared to the Poisson model. Stratum-specific weights from the matching algorithm were applied to all regression models to account for an unequal ratio of controls to onboarded patients across each stratum.

Sensitivity analyses

The first sensitivity analysis compared the impact on the primary model of changing the exclusion timeframe between ED attendance and admission/death from one day to i) the same day only or ii) within two days. All other model parameters remained the same.

A second sensitivity analysis for the primary model was conducted to assess for potential differences in COVID-19 specific outcomes between the enrolled and control groups, for two outcomes:

i. 28-day mortality using only deaths where COVID-19 (ICD-10 code U071) was listed as the primary cause of death.
ii. 28-day emergency hospital admissions where COVID-19 (ICD-10 code U071) was listed as a primary or secondary diagnosis.

Two sensitivity analyses were applied to the models for each of the logistic and negative binomial regression models:

1. A doubly robust model, adjusted for the matching variables, plus: smoking status, hypertension, chronic cardiac disease, chronic kidney disease, chronic respiratory disease, dementia, diabetes, chronic neurological disease (including epilepsy), learning disability, malignancy/immunosuppression, severe mental illness, peripheral vascular disease, stroke/TIA, the number of A&E attendances in the previous year, and the number of emergency hospital admissions in the previous year.
2. A covariate-adjusted model, adjusted for the same variables as the doubly robust model, but without use of the matching. This model included all enrolled patients, including those that were not matched in the primary analysis.

In adjusted models, IMD score was treated as deciles to give greater granularity from the terciles used in matching.

Table A1: Distribution of matching variables in 639 matched patients enrolled to CO@h after matching to controls, with p-value from chi-squared test comparing distribution in 19 unmatched patients (values not shown due to small numbers)

	Matched		p-value*
	Number	Percentage	
Age category (years)			
18-49	275	43.0%	0.002
50-64	246	38.5%	
65-79	94	14.7%	
80	24	3.8%	
Sex			
Female	331	51.8%	0.600
Male	308	48.2%	
Ethnicity			
White	495*	77.5%*	<0.001
Asian/Asian British	100*	15.6%*	
Black/African/Caribbean/Black British	15*	2.3%	
Mixed/Multiple ethnic groups	*	*	
Other ethnic group	20*	3.1%*	
IMD tercile			
1 (most deprived)	328	51.3%	0.086
2	196	30.7%	
3 (least deprived)	115	18.0%	
Body Mass Index			
Underweight	*	*	<0.001
Healthy weight	110*	17.2%*	
Overweight	215*	33.6%*	
Obese	315*	49.3%*	
Clinically extremely vulnerable (CEV) status			

Not CEV	533	83.4%	0.004
CEV	106	16.6%	
Month of COVID-19 test			
September/October	*	*	0.054
November	*	*	
December	30*	4.7%*	
January	360*	56.3%*	
February	165*	25.8%*	
March	55*	8.6%*	
April/May	15*	2.3%*	
Days from ED attendance to COVID-19 test			
-3 to -1 days	27	4.2%	0.403
0 to 4 days	302	47.3%	
5 to 10 days	310	48.5%	
Outcome measures:			
Deaths within 28 days	9	1.4%	0.176
At least one ED attendance within 28 days	192	30.0%	0.18
At least one admission within 28 days	152	23.8%	0.418
Critical care use of those admitted	9	1.4%	0.664
Total	**639**		

* Small values for non-missing data suppressed, and remaining values for variable rounded to nearest five

Table A2: Effect estimates associated with enrolment to CO@h for each study outcome after matching, in those aged 50 years or over

Outcome	Adjusted odds ratio	Standard error	p-value	95% confidence interval		Denominator
				Lower	Upper	
Death within 28 days	0.49	0.17	0.034	0.25	0.95	7,000
Any ED attendance within 28 days	1.28	0.15	0.031	1.02	1.61	7,000
Any hospital admission within 28 days	1.59	0.19	<0.001	1.26	2.01	7,000
Any level 2/3 care of those admitted	0.47	0.18	0.054	0.21	1.01	1,400
	Adjusted IRR*	**Standard error**	**p-value**	**Lower**	**Upper**	**Denominator**
Length of stay (days) of those admitted	0.928	0.086	0.421	0.774	1.113	1,268

*IRR = Incidence Rate Ratio

Table A3: Effect estimates associated with enrolment to CO@h for each study outcome after matching, applying exclusion of deaths and admissions on the same day as ED attendance only

Outcome	Adjusted odds ratio	Standard error	p-value	95% confidence interval		Denominator
				Lower	Upper	
Death within 28 days	0.61	0.10	0.004	0.44	0.86	26,659
Any ED attendance within 28 days	1.54	0.12	<0.001	1.32	1.80	26,659
Any hospital admission within 28 days	0.82	0.06	0.005	0.71	0.94	26,659
Any level 2/3 care of those admitted	0.90	0.15	0.518	0.66	1.24	11,879
	Adjusted IRR*	**Standard error**	**p-value**	**Lower**	**Upper**	**Denominator**
Length of stay (days) of those admitted	0.864	0.049	0.010	0.772	0.966	10,356

*IRR = Incidence Rate Ratio

Table A4: Effect estimates associated with enrolment to CO@h for each study outcome after matching, applying exclusion of deaths and admissions within two days of ED attendance

Outcome	Adjusted odds ratio	Standard error	p-value	95% confidence interval		Denominator
				Lower	Upper	
Death within 28 days	0.41	0.17	0.033	0.18	0.93	14,709
Any ED attendance within 28 days	1.18	0.12	0.095	0.97	1.43	14,709
Any hospital admission within 28 days	1.44	0.16	0.001	1.16	1.80	14,709
Any level 2/3 care of those admitted	0.22	0.13	0.010	0.07	0.70	1,637
	Adjusted IRR*	**Standard error**	**p-value**	**Lower**	**Upper**	**Denominator**
Length of stay (days) of those admitted	0.810	0.084	0.042	0.662	0.992	1,548

*IRR = Incidence Rate Ratio

Table A5: Sensitivity analysis of effect estimates associated with enrolment to CO@h on i) 28-day mortality where COVID-19 listed as primary cause of death and ii) 28-day hospitalisation where COVID-19 listed as primary or secondary diagnosis

Outcome	Adjusted odds ratio	Standard error	p-value	95% confidence interval		Denominator
				Lower	Upper	
Death within 28 days	0.50	0.19	0.071	0.24	1.06	15,507
Any hospital admission within 28 days	1.73	0.17	<0.001	1.43	2.10	15,621

Table A6: Numbers and percentages of smoking status, chronic conditions, and prior healthcare utilisation categories for enrolled patients and controls

Covariate	Controls		Enrolled		p-value
	N	%	N	%	
Smoking status					
Never smoker	8,471	56.5%	362	56.7%	0.433
Ex-smoker	4,003	26.7%	181	28.3%	
Current smoker	2,508	16.7%	96	15.0%	
Co-morbidities					
Hypertension	2,820	18.8%	165	25.8%	<0.001
Chronic cardiac disease	1,015	6.8%	62	9.7%	0.004
Chronic kidney disease	72	0.5%	*	*	<0.05
Chronic respiratory disease	4,437	29.6%	237	37.1%	<0.001
Dementia	61	0.4%	*	*	>0.50*
Diabetes	1,740	11.6%	117	18.3%	<0.001
Chronic neurological disease (including epilepsy)	698	4.7%	33	5.2%	0.554
Learning disability	113	0.8%	*	*	>0.50*
Malignancy or immunosuppression	1,168	7.8%	68	10.6%	0.009
Severe mental illness	539	3.6%	18	2.8%	0.297
Peripheral vascular disease	93	0.6%	10	1.6%	0.004
Stroke or TIA	342	2.3%	21	3.3%	0.099
Number of ED attendances in the year before COVID-19					
0	9,677	64.6%	435*	68.1%*	0.05 – 0.50*
1	2,846	19.0%	105*	16.4%*	

2	1,165	7.8%	50*	7.8%*	
3-4	787	5.3%	35*	5.5%*	
5-9	365	2.4%	15*	2.3%*	
10 or more	142	0.9%	*	*	
Number of emergency hospital admissions in the year before COVID-19					
0	13,068	87.2%	555*	86.9%*	>0.50*
1	1252	8.4%	55*	8.6%*	
2	364	2.4%	15*	2.3%*	
3	136	0.9%	*	*	
4 or more	162	1.1%	*	*	
Total	**14,982**		**639**		

* Small values for non-missing data suppressed, and remaining values for variable rounded to nearest five; p-values reported as <0.05, 0.05–0.5, or >0.5.

Table A7: Effect estimates associated with enrolment to CO@h for each study outcome from covariate adjusted models (unmatched)

Outcome	Adjusted odds ratio	Standard error	p-value	95% confidence interval		Denominator
				Lower	Upper	
Death within 28 days	0.48	0.16	0.031	0.24	0.94	56,793
Any ED attendance within 28 days	1.32	0.12	0.002	1.11	1.58	56,793
Any hospital admission within 28 days	1.59	0.16	<0.001	1.31	1.93	56,793
Any level 2/3 care of those admitted	0.50	0.17	0.047	0.25	0.99	9,185
	Adjusted IRR*	**Standard error**	**p-value**	**Lower**	**Upper**	**Denominator**
Length of stay (days) of those admitted	0.982	0.080	0.825	0.84	1.15	8,300

*IRR = Incidence Rate Ratio

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Appendix A

Evaluating the impact of a pulse oximetry remote monitoring programme on mortality and healthcare utilisation in patients with COVID-19 assessed in Emergency Departments in England: a retrospective matched cohort study

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Entry criteria for COVID Oximetry @home

Eligibility for the COVID Oximetry @home (CO@h) programme is defined in the NHS England Standard Operating Procedure (SOP) although there was flexibility is operational models and eligibility across sites.[1]

Monitoring requirements could vary across sites, and involve text messages, email prompts or check-in calls, or support for full self-management and escalation.[1] Pulse oximeters were purchased by individual sites, or requested from the NHS Supply Chain and were required to meet ISO 80601-2-61:2017 and be CE marked.[1]

Data cleaning

Note: the described datasets were used for several distinct analyses by the study team, with data cleaning rules the same or similar between studies. For this reason, some of the text in the appendices may be identical to that of other published articles by the study authors on the same data source.

COVID-19 testing data

Testing data was provided through the Public Health England Second Generation Surveillance System (SGSS). This dataset captures routine laboratory data on infectious diseases for England, including COVID-19, with all diagnostic laboratories required to notify positive test results within 24 hours.[2] Data included 3,251,225 tests performed from 1st October 2020 to 30th June 2021, inclusive.

Provided data included test date and result date. 99% of results were reported within 5 days of the test, and 6,544 (0.2%) were reported more than 7 days from date of test. Where the result data occurred before the test date. In 1,603 cases, the result date was recorded as prior to the test date. In these instances, where the difference between the testing date and reporting date was 7 days or less, the test date and reporting date were swapped. In the 191 instances where reporting date was more than 7 days before the testing date, the test was excluded.

For this analysis, only tests performed up to 3rd May 2021 were included (after swapping test and result dates where applicable), given that secondary care data was available up until the end of May 2021. Of the 2,928,802 positive COVID-19 tests, 2,352,390 (80.3%) were from Pillar 2 testing, 561,852 (19.2%) from Pillar 1, and 14,560 (0.5%) from Pillar 4.[3] Test type was recorded for Pillar 2 tests only, and of these, 2,250,288 (95.7%) were Polymerase Chain Reaction (PCR) tests, 102,102 (4.3%) were lateral flow tests.

For this analysis, only the first positive test was taken where more than one was recorded for any given individual, resulting in a total eligible population of 2,536,322.

COVID Oximetry @home (CO@h) programme data

Data on patients enrolled ('onboarded') onto the CO@h programme were submitted directly from CO@h sites via NHS Digital's Strategic Data Collection Service.[4] Data included a deidentified NHS patient ID of the patient onboarded, along with the date of onboarding to and offboarding from the programme. Any patient with an offboarding date but no onboarding date were excluded from the analyses.

Shielded Patient List

Identification of high-risk patients, designated 'Clinically Extremely Vulnerable' (CEV) was provided via a linkage from the NHS Digital Shielded Patient List (SPL) to the primary care record.[5] Patients with any of the conditions listed in Box A1 below were designated as high risk.[6] Code lists for the conditions are available to download from NHS Digital.[7] In addition, from February 2021, people were also added to the list if identified as high risk using the QCovid risk prediction model, which combines factors including age, sex, ethnicity, BMI as well as specific conditions.[8] Thresholds of mortality risk for inclusion in the SPL were an absolute risk of 0.5% or higher, or a relative risk of 10 times the baseline risk of a person with the same age and sex.[6] GP practices and NHS Trusts were also able to add and remove patients from the SPL based on clinical judgment and individual risk assessments.[9]

Box A1: NHS Digital criteria for Clinically Extremely Vulnerable patients:

- solid organ transplant recipients
- people with severe respiratory conditions including all cystic fibrosis, severe asthma and severe chronic obstructive pulmonary (COPD)
- people with rare diseases and inborn errors of metabolism that significantly increase the risk of infections (such as Severe combined immunodeficiency (SCID), homozygous sickle cell)
- people on immunosuppression therapies sufficient to significantly increase risk of infection
- people who have problems with their spleen, for example have had a splenectomy
- adults with Down's syndrome
- adults on dialysis with kidney impairment (Stage 5 Chronic Kidney Disease)
- women who are pregnant with significant heart disease, congenital or acquired
- people with cancer who are undergoing active chemotherapy
- people with lung cancer who are undergoing radical radiotherapy
- people with cancers of the blood or bone marrow such as leukaemia, lymphoma or myeloma who are at any stage of treatment
- people having immunotherapy or other continuing antibody treatments for cancer
- people having other targeted cancer treatments which can affect the immune system, such as protein kinase inhibitors or PARP inhibitors
- people who have had bone marrow or stem cell transplants in the last 6 months, or who are still taking immunosuppression drugs

Source: https://digital.nhs.uk/coronavirus/shielded-patient-list/risk-criteria

Primary care data

Primary care data came from the General Practice Extraction Service (GPES) Data for Pandemic Planning and Research (GDPPR).[10] Data included month and year of birth, sex, ethnicity, Lower Layer Super Output Area (LSOA) of residence, a marker for Clinically Extremely Vulnerable (CEV) status, and a marker for residence in a care home. LSOA was used to link to 2019 deciles of Index of Multiple Deprivation (IMD).[11] Age was calculated from date of positive COVID-19 test, assuming a birthdate on the 15th day of the month.

Entries include a date to which each journal item applies, and a date on which the journal item was recorded. The former was used in priority, but where missing, was replaced with the journal item recording date. For LSOA, CEV status and care home residence, only entries occurring up to the date of positive COVID-19 test were included. For month and year of birth, sex and ethnicity, if no entry were included prior to the date of COVID-19 test, then the earliest recorded entry after the test was included.

Secondary care data

Data on hospital admissions came from the Hospital Episode Statistics (HES) data set up to 31st May 2021, linked to Office for National Statistics (ONS) data on death registrations up to 5th July 2021.[12] Entries were excluded where missing admission dates, provider Trust code, or patient deidentified ID.

Where multiple admission episodes were recorded within a spell, a single spell start and end date were created. Non-emergency hospital admissions were excluded from analyses. A binary indicator was created for any admission within 28 days of positive COVID-19 test. A second indicator was created for death (of any cause) within 28 days of positive COVID-19 test. Critical care admissions were defined as an admission episode for any level 2 or level 3 care within the defined spell.

Data on accident and emergency (A&E) attendances came from the Emergency Care Data Set (ECDS).[13] Only A&E presentations to NHS providers were selected (Trust codes beginning with 'R'). The A&E attendance date, departure date and admission date (if subsequently admitted) are included. In cases where attendance date was recorded as being

after the departure date, the attendance date was set to the departure date, if departure date was equal to the admission date. Otherwise, attendance date was assumed to be correct. Where multiple A&E attendances were recorded on the same day, a single attendance was kept for each patient, prioritising in turn:

1. Any attendance associated with an admission
2. Earliest time of attendance
3. Earliest time of departure

A binary indicator was created for one or more A&E attendances within 28 days of a positive COVID-19 test.

Where age was missing from GDPPR, it was derived from month and year of birth in HES, or if also missing in HES, derived from month and year of birth in ECDS, using the same approach as for GDPPR. Where LSOA was missing from GDPPR, it was derived from HES/ECDS. CCG was derived first from testing data, and if missing, from CO@h programme data, followed by GDPPR/HES/ECDS if missing.

Co-morbidities

SNOMED codes were included in the GDPPR dataset pertaining to specific SNOMED code cluster reference sets provided by NHS Digital.[10] 6,485 unique codes were identified from GDPPR. Codes were reviewed manually by authors TB and JC and removed if not relevant or assigned to the minimal number of relevant code clusters.

SNOMED reference clusters were aggregated into hierarchies of similar conditions. Codes in each higher-order cluster were then reviewed to ensure groupings of relevant codes and twelve relevant chronic disease categories were selected: hypertension, chronic cardiac disease, chronic kidney disease, chronic respiratory disease, dementia, diabetes, chronic neurological disease (including epilepsy), learning disability, malignancy/immunosuppression, severe mental illness, peripheral vascular disease and stroke/transient ischaemic attack (TIA). Categories for chronic respiratory disease, diabetes, epilepsy, malignancy/immunosuppression and severe mental illness included relevant medication codes. Broad diagnostic categories of diagnoses were chosen, as certain

medications were not diagnostic of more granular diagnostic categories (for example, use of a long-acting bronchodilator/inhaled corticosteroid in both COPD and asthma).

For each patient in GDPPR, all relevant diagnostic codes prior to the study index date (date of positive COVID-19 test) were considered diagnostic. In cases where the latest SNOMED code indicated resolution of a condition (e.g. 'Atrial fibrillation resolved (finding)'), then the diagnosis was excluded for that patient. SNOMED codes relating to drug codes were only included up to 2 years prior to the index date.

A full list of codes within each diagnostic category are available in our GitHub repository: https://github.com/tbeaney/Imperial-COh-evaluation

BMI categorisation

SNOMED codes for BMI were either diagnostic categories (eg 'Body mass index 30+ - obesity (finding)' or value codes (e.g. 'Body mass index (observable entity)'). Values were extracted and BMI was categorised according to the standard World Health Organisation classification of underweight (<18.5 kg/m^2), healthy weight (18.5-24.9 kg/m^2), overweight (25.0-29.9 kg/m^2) and obese (≥30.0 kg/m^2). Value codes outside of the range 5.0-100.0 kg/m2 were excluded. SNOMED codes which spanned more than one category (e.g. 'Increased body mass index (finding)') and child BMI categories were also excluded.

Smoking categorisation

Smoking status was categorised into 'never-smoker', 'ex-smoker' and 'current smoker' according to the latest SNOMED code prior to and including the index date. For any patient where the latest SNOMED code indicated 'never-smoker', but a prior record indicated active smoking, then the patient was re-categorised as 'ex-smoker.

Statistical analysis

For the matched analysis, enrolled patients ('treated') were matched with patients who were not enrolled ('controls'), using the *cem* command in Stata following the approach defined by Blackwell et al (2010).[14] Patients with any of the matching variables missing (8,255; 12.7%) were dropped for the analysis, resulting in a total of 56,135 controls and 658 treated.

The following variables were chosen *a priori* for inclusion in the matching algorithm:

- Age category (<50, 50-64, 65-79, 80+ years)
- Sex (female or male)
- Ethnicity (using the five ONS categories: White, Asian/Asian British, Black/African/Caribbean/Black British, Mixed/Multiple ethnic groups, Other ethnic groups)
- Terciles of IMD score
- BMI category (underweight, healthy weight, overweight, obese)
- Month of ED index date (September-October 2020 & April-May 2021 were combined due to small numbers in September and May)
- Clinically Extremely Vulnerable (CEV) status (yes/no)
- Days from COVID-19 test to A&E index date (cuts applied at: -3 to -1; 0 to 4; 5 to 10 days)

Logistic regression was used to estimate the treatment effect of the programme separately for each of the four binary outcomes occurring in the time period from A&E index date to 28 days:

- Death from any cause
- Any ED attendance (excluding the ED index attendance)
- Any emergency hospital admission
- Any critical care (level 2 or level 3) admission, of those admitted

Negative binomial regression was used to estimate the treatment effect of the programme on length of stay in days, for those admitted within 28 days. Total length of stay was capped at 28 days where a patient was discharged after the 28-day window, and analyses of length of stay excluded patients who died within the 28-day time window. The overdispersion parameter was calculated and the distribution of length of stay was found to be overdispersed

compared to a Poisson process in all models, indicating superior model fit for the negative binomial model compared to the Poisson model. Stratum-specific weights from the matching algorithm were applied to all regression models to account for an unequal ratio of controls to onboarded patients across each stratum.

Sensitivity analyses

The first sensitivity analysis compared the impact on the primary model of changing the exclusion timeframe between ED attendance and admission/death from one day to i) the same day only or ii) within two days. All other model parameters remained the same.

A second sensitivity analysis for the primary model was conducted to assess for potential differences in COVID-19 specific outcomes between the enrolled and control groups, for two outcomes:

i. 28-day mortality using only deaths where COVID-19 (ICD-10 code U071) was listed as the primary cause of death.
ii. 28-day emergency hospital admissions where COVID-19 (ICD-10 code U071) was listed as a primary or secondary diagnosis.

Two sensitivity analyses were applied to the models for each of the logistic and negative binomial regression models:

1. A doubly robust model, adjusted for the matching variables, plus: smoking status, hypertension, chronic cardiac disease, chronic kidney disease, chronic respiratory disease, dementia, diabetes, chronic neurological disease (including epilepsy), learning disability, malignancy/immunosuppression, severe mental illness, peripheral vascular disease, stroke/TIA, the number of A&E attendances in the previous year, and the number of emergency hospital admissions in the previous year.
2. A covariate-adjusted model, adjusted for the same variables as the doubly robust model, but without use of the matching. This model included all enrolled patients, including those that were not matched in the primary analysis.

In adjusted models, IMD score was treated as deciles to give greater granularity from the terciles used in matching.

Table A1: Distribution of matching variables in 639 matched patients enrolled to CO@h after matching to controls, with p-value from chi-squared test comparing distribution in 19 unmatched patients (values not shown due to small numbers)

	Matched		p-value*
	Number	Percentage	
Age category (years)			
18-49	275	43.0%	0.002
50-64	246	38.5%	
65-79	94	14.7%	
80	24	3.8%	
Sex			
Female	331	51.8%	0.600
Male	308	48.2%	
Ethnicity			
White	495*	77.5%*	<0.001
Asian/Asian British	100*	15.6%*	
Black/African/Caribbean/Black British	15*	2.3%	
Mixed/Multiple ethnic groups	*	*	
Other ethnic group	20*	3.1%*	
IMD tercile			
1 (most deprived)	328	51.3%	0.086
2	196	30.7%	
3 (least deprived)	115	18.0%	
Body Mass Index			
Underweight	*	*	<0.001
Healthy weight	110*	17.2%*	
Overweight	215*	33.6%*	
Obese	315*	49.3%*	
Clinically extremely vulnerable (CEV) status			

Not CEV	533	83.4%	0.004
CEV	106	16.6%	
Month of COVID-19 test			
September/October	*	*	0.054
November	*	*	
December	30*	4.7%*	
January	360*	56.3%*	
February	165*	25.8%*	
March	55*	8.6%*	
April/May	15*	2.3%*	
Days from ED attendance to COVID-19 test			
-3 to -1 days	27	4.2%	0.403
0 to 4 days	302	47.3%	
5 to 10 days	310	48.5%	
Outcome measures:			
Deaths within 28 days	9	1.4%	0.176
At least one ED attendance within 28 days	192	30.0%	0.18
At least one admission within 28 days	152	23.8%	0.418
Critical care use of those admitted	9	1.4%	0.664
Total	**639**		

* Small values for non-missing data suppressed, and remaining values for variable rounded to nearest five

Table A2: Effect estimates associated with enrolment to CO@h for each study outcome after matching, in those aged 50 years or over

Outcome	Adjusted odds ratio	Standard error	p-value	95% confidence interval		Denominator
				Lower	Upper	
Death within 28 days	0.49	0.17	0.034	0.25	0.95	7,000
Any ED attendance within 28 days	1.28	0.15	0.031	1.02	1.61	7,000
Any hospital admission within 28 days	1.59	0.19	<0.001	1.26	2.01	7,000
Any level 2/3 care of those admitted	0.47	0.18	0.054	0.21	1.01	1,400
	Adjusted IRR*	**Standard error**	**p-value**	**Lower**	**Upper**	**Denominator**
Length of stay (days) of those admitted	0.928	0.086	0.421	0.774	1.113	1,268

*IRR = Incidence Rate Ratio

Table A3: Effect estimates associated with enrolment to CO@h for each study outcome after matching, applying exclusion of deaths and admissions on the same day as ED attendance only

Outcome	Adjusted odds ratio	Standard error	p-value	95% confidence interval		Denominator
				Lower	Upper	
Death within 28 days	0.61	0.10	0.004	0.44	0.86	26,659
Any ED attendance within 28 days	1.54	0.12	<0.001	1.32	1.80	26,659
Any hospital admission within 28 days	0.82	0.06	0.005	0.71	0.94	26,659
Any level 2/3 care of those admitted	0.90	0.15	0.518	0.66	1.24	11,879
	Adjusted IRR*	**Standard error**	**p-value**	**Lower**	**Upper**	**Denominator**
Length of stay (days) of those admitted	0.864	0.049	0.010	0.772	0.966	10,356

*IRR = Incidence Rate Ratio

Table A4: Effect estimates associated with enrolment to CO@h for each study outcome after matching, applying exclusion of deaths and admissions within two days of ED attendance

Outcome	Adjusted odds ratio	Standard error	p-value	95% confidence interval		Denominator
				Lower	Upper	
Death within 28 days	0.41	0.17	0.033	0.18	0.93	14,709
Any ED attendance within 28 days	1.18	0.12	0.095	0.97	1.43	14,709
Any hospital admission within 28 days	1.44	0.16	0.001	1.16	1.80	14,709
Any level 2/3 care of those admitted	0.22	0.13	0.010	0.07	0.70	1,637
	Adjusted IRR*	**Standard error**	**p-value**	**Lower**	**Upper**	**Denominator**
Length of stay (days) of those admitted	0.810	0.084	0.042	0.662	0.992	1,548

*IRR = Incidence Rate Ratio

Table A5: Sensitivity analysis of effect estimates associated with enrolment to CO@h on i) 28-day mortality where COVID-19 listed as primary cause of death and ii) 28-day hospitalisation where COVID-19 listed as primary or secondary diagnosis

Outcome	Adjusted odds ratio	Standard error	p-value	95% confidence interval		Denominator
				Lower	Upper	
Death within 28 days	0.50	0.19	0.071	0.24	1.06	15,507
Any hospital admission within 28 days	1.73	0.17	<0.001	1.43	2.10	15,621

Table A6: Numbers and percentages of smoking status, chronic conditions, and prior healthcare utilisation categories for enrolled patients and controls

Covariate	Controls		Enrolled		p-value
	N	%	N	%	
Smoking status					
Never smoker	8,471	56.5%	362	56.7%	0.433
Ex-smoker	4,003	26.7%	181	28.3%	
Current smoker	2,508	16.7%	96	15.0%	
Co-morbidities					
Hypertension	2,820	18.8%	165	25.8%	<0.001
Chronic cardiac disease	1,015	6.8%	62	9.7%	0.004
Chronic kidney disease	72	0.5%	*	*	<0.05
Chronic respiratory disease	4,437	29.6%	237	37.1%	<0.001
Dementia	61	0.4%	*	*	>0.50*
Diabetes	1,740	11.6%	117	18.3%	<0.001
Chronic neurological disease (including epilepsy)	698	4.7%	33	5.2%	0.554
Learning disability	113	0.8%	*	*	>0.50*
Malignancy or immunosuppression	1,168	7.8%	68	10.6%	0.009
Severe mental illness	539	3.6%	18	2.8%	0.297
Peripheral vascular disease	93	0.6%	10	1.6%	0.004
Stroke or TIA	342	2.3%	21	3.3%	0.099
Number of ED attendances in the year before COVID-19					
0	9,677	64.6%	435*	68.1%*	0.05 – 0.50*
1	2,846	19.0%	105*	16.4%*	

2	1,165	7.8%	50*	7.8%*	
3-4	787	5.3%	35*	5.5%*	
5-9	365	2.4%	15*	2.3%*	
10 or more	142	0.9%	*	*	
Number of emergency hospital admissions in the year before COVID-19					
0	13,068	87.2%	555*	86.9%*	>0.50*
1	1252	8.4%	55*	8.6%*	
2	364	2.4%	15*	2.3%*	
3	136	0.9%	*	*	
4 or more	162	1.1%	*	*	
Total	**14,982**		**639**		

* Small values for non-missing data suppressed, and remaining values for variable rounded to nearest five; p-values reported as <0.05, 0.05–0.5, or >0.5.

Table A7: Effect estimates associated with enrolment to CO@h for each study outcome from covariate adjusted models (unmatched)

Outcome	Adjusted odds ratio	Standard error	p-value	95% confidence interval		Denominator
				Lower	Upper	
Death within 28 days	0.48	0.16	0.031	0.24	0.94	56,793
Any ED attendance within 28 days	1.32	0.12	0.002	1.11	1.58	56,793
Any hospital admission within 28 days	1.59	0.16	<0.001	1.31	1.93	56,793
Any level 2/3 care of those admitted	0.50	0.17	0.047	0.25	0.99	9,185
	Adjusted IRR*	**Standard error**	**p-value**	**Lower**	**Upper**	**Denominator**
Length of stay (days) of those admitted	0.982	0.080	0.825	0.84	1.15	8,300

*IRR = Incidence Rate Ratio

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