Supplementary file 1 – Detailed methods

Workstream 1 – Methods for COVID Oximetry @home evaluation and results from sensitivity analysis

Methods

Study design

The study of overall mortality and admissions was designed as an area-level analysis combining aggregated data from different sources. Considering these data as time series, we investigated "dose-response" relationships [2] between the evolving enrolment of people to the programme within each area and outcome. We analysed four outcomes: mortality from COVID-19, hospital admissions for people with confirmed or suspected COVID-19, in-hospital mortality for these admissions and their LOS. For the in-hospital outcomes, we used an observational design relating in-hospital mortality and lengths of stay at an individual patient level to the level of enrolment to the CO@h programme within the area at the time of admission.

Setting and participants

The setting was all CCG areas in England where there was complete data on the number of people enrolled on to the programme (onboarded) between 2nd November 2020 and 21st February 2021. (CCGs are NHS organisations that organise the delivery of primary care services within a specific geographic area. At the time of the study there were 135 in England.) The study populations included anyone with a laboratory-confirmed positive test for COVID-19 and any hospital admission for COVID-19 or suspected COVID-19. We also limited the analysis to people aged 65 or over, as this population was eligible for CO@h across all CCGs and both enrolment and frequency of outcomes within this group were higher. Implementation among younger age groups across the country was much more variable.

Data and variables

For our analysis we used data from several sources (Table 1). Data on numbers of new cases of COVID-19 and deaths were acquired from PHE (now the UK Health Security Agency). New cases were laboratory-confirmed and deaths were those either within 60 days of the first positive test or where COVID-19 was mentioned on the death certificate.[3] If someone had more than one positive test within the previous seven days, then only one was counted.[4] These data were aggregated by week, age band and CCG. The selected age bands were 65 to 79 and 80 plus. Numbers of people onboarded to CO@h were sourced from a bespoke national data collection for the programme and aggregated by the team at Imperial College London undertaking one of the other two simultaneous evaluations.[5, 6] Due to small numbers, aggregation was performed by fortnight, rather than week, and by the same age bands and by CCG. To comply with data protection rules, these data were also rounded to the nearest five individuals, or, for smaller values, labelled as between one and seven. For these smaller values we assigned a value of four, being the mid-point within the range.

Table 1: Sources of data and information used in the study.

Data	Source	Details
Mortality within 60 days of first laboratory-confirmed case or with confirmed COVID-19 present on death certificate	PHE (Now UK Health Security Agency)	By age band, CCG, week

New cases of laboratory-confirmed COVID-19	PHE	By age band, CCG, week
People onboarded to CO@h	NHS Digital: bespoke data collection from the programme aggregated by Imperial College London	By age band, CCG and fortnight, rounded to the nearest five patients or labelled as between one and seven
Hospital admissions for COVID-19 or suspected COVID-19	HES	Individual patient-level data aggregated by age band, fortnight and CCG of responsibility
In-hospital mortality	HES	Individual patient-level data
LOS	HES	Individual patient-level data
Patient characteristics on admission	HES	Individual patient-level data
The proportion of acute beds occupied patients with COVID-19	NHS England and NHS Improvement	By acute trust, daily
The presence of a post-discharge CVW	Kent, Surrey and Sussex AHSN	By acute trust

Data on hospital admissions and outcomes were obtained from HES. Although most of the non-hospital data were available weekly, we aggregated to fortnightly data in order to match the aggregation of the onboarding data. We restricted our statistical analysis to the period between 2 November 2020 and 21 February 2021 when numbers of cases and outcomes were at their peak. Also, outside that period there were too many low numbers at our chosen level of granularity.

Rates of enrolment to CO@h were measured as numbers joining the programme within each CCG every fortnight divided by the number of new cases detected in that fortnight. To be able to calculate this by CCG, we required the onboarding data within a CCG to be complete.

To judge completeness of data we combined three sources of information:

(i) The management information collected by NHS Digital from each site;
(ii) Onboarding data received by the programme (the programme data); and
(iii) Replies to the costing survey administered by the study team and sent to 28 sites.

The management information provided assessments as to whether the data reported by each site were complete up to mid-April 2021, the onboarding data covered the period from October 2020 to the end of April 2021 and the survey asked for numbers of individuals onboarded from the date the service started up to the end of April 2021.

With the costing survey, sites were independently asked how many people they had onboarded, and we used this information to validate the reports of completeness from the national programme and to include additional CCGs where the numbers onboarded were broadly similar or greater. For most sites the numbers were broadly similar. However, among the CCGs reported as complete in the management information, we excluded three CCGs where the numbers onboarded in the programme data were below 60% of those in the survey. We also included three CCGs where the data were not reported as complete but the numbers recorded as onboarded within the programme data were approximately the same as, or exceeded the numbers in the survey.

The proportion of hospital beds occupied by COVID-19 patients was used as a measure of local system pressures and sourced from publicly available routine data. [7] By the end of February 2021, most hospital trusts were operating step-down virtual wards whereby COVID-19 patients could be discharged early with a pulse oximeter and monitored at home in a similar way to the CO@h service. [8] Due to the potential influence of these virtual wards on hospital outcomes, their existence was incorporated as a confounding variable in our analyses of length of stay and in-hospital mortality.

Enrolment to CO@h

We estimated enrolment in two ways. One was to calculate it for each CCG regardless of whether a service was operating at the time, and this was used in our analysis. The other measure of enrolment was an estimate of what was achievable once a service was implemented. For this we only included fortnights over which a service was operating within the CCG for the entirety. Because the data was fortnightly, it was not clear during the first fortnight when a site started onboarding patients. Therefore, to calculate enrolment rates after implementation, we started from the second fortnight.

Comparisons between included and excluded CCGs

We compared population characteristics and COVID-19 incidence rates between the CCGs we included because their data were believed to be complete, and the remaining CCGs to test how representative the included CCGs were. The mean values and proportions associated with each CCG were treated as the separate observations and comparisons were carried out using Student t-test, or Mann-Whitney U-tests where data were skewed. We also investigated their geographical spread.

Analysis of mortality

Because we only had aggregate data for deaths, new COVID cases and people onboarded to CO@h, our approach was to calculate enrolment rates to CO@h over time and then investigate relationships between levels of enrolment and mortality by age band within each CCG. To do this we adopted a two-stage approach. The first stage was to estimate denominators representing exposure, the second was to use these as offset variables in negative binomial regression models, relating mortality to enrolment to the CO@h programme by age group. We included a further variable for the month to allow for changes in relationships as the second wave progressed. To account for CCG-level effects we used GEE approaches with an exchangeable correlation structure.[9] This approach accommodates the fact that mortality within a single CCG is likely to be correlated and GEEs ensure that correlation is accounted for by adjusting parameter estimates and standard errors.

The need to estimate denominators arose because we were not able to directly link the new cases and mortality data. When a death occurs, the median time between a new case arising and death is about two weeks, although some may have been diagnosed only in the previous week, and some three weeks or more before. We therefore developed a preliminary set of regression models relating mortality to new cases, with new cases lagged at different times, in order to establish the contributions of the lagged variables. These then determined weights which we used to aggregate new cases into a denominator. Assuming that there was no lag between diagnosis and exposure to the programme, we applied the same weights to the onboarding data to establish a weighted enrolment variable appropriate to the mortality observed at each time. This process is described in more detail in the section *'Estimating the exposure components of the regression models' below.*

Other options for lagging the time between diagnosis, onboarding and mortality were tested in sensitivity analysis.

Analysis of hospital admissions

Hospital admissions over the study period were extracted from HES. We considered any admission where COVID-19 or suspected COVID-19 appeared as a diagnosis in the first episode of care, whether as a primary or secondary diagnosis (ICD-10 codes U07.1 and U07.2). If a patient was readmitted with one of these diagnoses within a 28-day period, we only considered the first admission. To match the onboarding data, numbers were aggregated by age band and fortnight.

We undertook a similar procedure for hospital admissions as for mortality, although with different weights, since the time between diagnosis and admission tended to be shorter.

Again, for our sensitivity analysis, we tested different options for lagging the time between diagnosis, onboarding and outcomes. We also tested the option of only including admissions where COVID-19 or suspected COVID-19 was the primary diagnosis.

Separate models were developed to evaluate any impact of CO@h on the characteristics of patients admitted in terms of age, sex, deprivation, Charlson Score (a measure of the severity of co-morbidities) and ethnicity.

Our dependent variables for these characteristics were mean age of admissions by CCG, numbers of female admissions, numbers living in the most deprived quintile defined by the Index of Multiple Deprivation (IMD), numbers with Charlson scores greater than five and numbers reported with non-white ethnicity. For age, we performed ordinary linear regression relating the mean age to enrolment and month accounting for CCG-level effects using GEE approaches, as before. For the other characteristics we used Poisson regression to relate each dependent variable to enrolment, age band and month and accounting for CCG-level effects in a similar way. For the Poisson regression models, the natural logarithm of the number of admissions was used as an offset variable.

Analysis of In-hospital outcomes

To analyse outcomes for COVID-19 patients admitted to hospital, we used individual-level HES. To measure in-hospital mortality, we included any death that was reported within the same hospital spell. To investigate the impact on in-hospital mortality, we created logistic regression models relating mortality to the weighted enrolment to the relevant CCG with individual patient characteristics as confounders. Values for the weighted enrolment corresponded to those calculated for hospital admissions. Again, we used GEE approaches to account for CCG-level effects. Length of stay was defined as the number of days between admission and discharge from the same hospital or death within that hospital. We used negative binomial regression models [10] to analyse the impact on lengths of stay of the weighted enrolment to the relevant CCG, again with individual patient characteristics as confounders. Stays longer than 60 days were trimmed to 60 days to mitigate the influence of very long stays. Because we used negative binomial models, the impact on length of stay was measured as percentage changes rather than numbers of days.

Estimating the exposure components of the regression models

For our modelling of mortality and hospital admission we required estimates of exposure to COVID-19 so that we could then relate rates of outcome to levels of enrolment and other variables. For example, for mortality, the basic regression model used is:

$$Log(number\ of\ deaths(t)) = Log(Exposure(t)) + \beta_0 + \beta_1(Coverage(t)) + \beta_2(Age\ band) + \beta_3(Month)$$

where the β_i's are regression coefficients and *t* denotes the fortnight.

A simple approach would be to estimate exposure as the number of new cases in the same period as the deaths occurred, but, given many of those dying would have been identified as new cases some weeks before, this is unrealistic and would overestimate the exposure while cases are rising and underestimate it when cases are falling. A better approach would be to recognise the median time between diagnosis and death as about two weeks, and so use the number of new cases in the previous fortnight. In our study we went a further step and implemented an approach that applied weights to the case data from more than one previous time period. These weights reflect the relative contributions of each time period, sum to one, and can be estimated by linear regression, assuming the relationship remains constant over the period of the analysis (Figure 1).

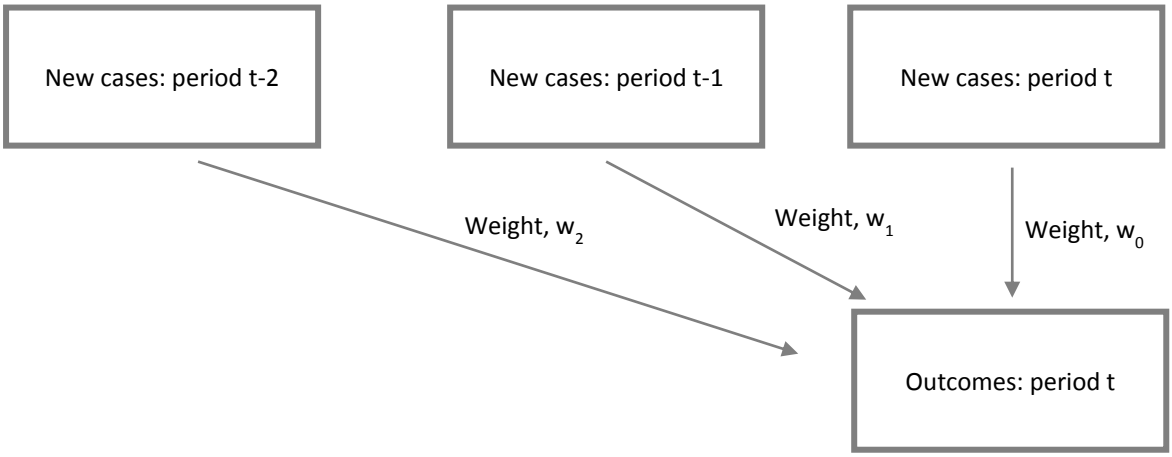

Figure 1: The application of weights to the current and previous time periods (fortnights) to create the exposure associated with outcomes. The sum of weights: $w_0 + w_1 + w_2 = 1$.

Assuming onboarding into the CO@h programme occurs soon after diagnosis, the lags and corresponding weights used for the onboarding data remain the same. The weighted onboarding numbers divided by the weighted new cases then becomes the enrolment rate that is used in the final regression model shown above.

The weights that we used are shown in Table 2. If we included lags of more than two fortnights, the estimated weights for those periods became very small and lacked statistical significance, so we carried out our final estimates by only going back as far as two previous fortnights. Different weightings were selected for the sensitivity analysis to see how they affected results.

Table 2: Weights applied to lagged numbers of new cases for each outcome. (w_0 is applied to new cases in the same period as the outcome is measured, w_1 is applied to new cases in the previous fortnight and w_2 to the fortnight before that).

		Weight		
Outcome	**Age band**	**w_0**	**w_1**	**w_2**
Mortality	65 to 79	23.1%	60.2%	16.6%
	80+	27.5%	67.4%	5.0%
Hospital admission	65 to 79	61.1%	37.8%	1.1%
	80+	81.8%	14.5%	3.7%

Using rounded data

To accommodate the uncertainty caused by the rounding of the onboarding data, we ran all our statistical models multiple times, each time randomly sampling onboarded numbers from the range of feasible values (treating the distributions as uniform). Based on the similarity of results with each simulation, we deemed it sufficient to perform 1000 runs for each model. The simulation results were then pooled to obtain overall effect sizes. All statistical analyses were performed using SAS version 9.4.[11]

Data governance and ethics

The receipt of aggregated data from PHE was governed by a data sharing agreement. Receipt of aggregated onboarding data from Imperial College was governed by their separate data sharing agreement with NHS Digital. The access and use of HES was governed by an existing data sharing agreement with NHS Digital covering NIHR RSET analysis (DARS-NIC-194629-S4F9X). Since we were using combinations of aggregated data and datasets for which we already had approval to use, no ethics committee approval was needed for this analysis.

Sensitivity analysis

For sensitivity analysis we tested different scenarios for weighting lagged variables to create different values for exposure in our regression models. We also investigated outcomes if we excluded hospital admissions for suspected COVID-19, focusing exclusively on confirmed diagnoses. For the weighting scenarios we chose the same weighting for both age bands and varied them across a range of feasible values. For the in-hospital outcomes the weightings are applied to the enrolment rates and correspond to those for admissions.

Under each scenario, the impacts of a 10% increase in enrolment on each outcome are shown in Tables 3-5. None of the effects are statistically significant at the 5% level (two-sided), although the impact on the risk of hospital admission without any lags (w_0 = 100%, w_1 = 0%, w_2 = 0%), or with a lag of just one fortnight (w_0 = 0%, w_1 = 100%, w_2 = 0%) are borderline significant for a positive relationship (p=0.06 in both scenarios).

Table 3: The impact of patient enrolment rates on the risk of mortality under different modelling assumptions.

Scenario		**Relative risk of death associated with a 10% increase in enrolment *(95% confidence interval)***	
Baseline	(see *Table 2*)	0.98	*(0.96, 1.01)*
Weighting (applied to both age bands)	w_0 = 30%, w_1 = 50%, w_2 = 20%	0.98	*(0.95, 1.01)*
	w_0 = 10%, w_1 = 70%, w_2 = 20%	0.98	*(0.95, 1.01)*
	w_0 = 30%, w_1 = 70%, w_2 = 0%	1.00	*(0.97, 1.03)*
	w_0 = 0%, w_1 = 100%, w_2 = 0%	1.00	*(0.97, 1.02)*

Table 4: The impact of patient enrolment rates on the occurrence of hospital admission under different modelling assumptions.

Scenario		**Relative risk of admission associated with a 10% increase in enrolment *(95% confidence interval)***	
Baseline	(see *Table 2*)	1.03	*(0.99, 1.07)*
Weighting (applied to both age bands)	w_0 = 60%, w_1 = 40%, w_2 = 0%	1.02	*(0.98, 1.06)*
	w_0 = 100%, w_1 = 0%, w_2 = 0%	1.03	*(1.00, 1.07)*
	w_0 = 0%, w_1 = 100%, w_2 = 0%	1.05	*(1.00, 1.10)*
	w_0 = 50%, w_1 = 50%, w_2 = 0%	1.02	*(0.98, 1.06)*
	w_0 = 60%, w_1 = 30%, w_2 = 10%	1.01	*(0.97, 1.05)*
Exclude patients with suspected COVID-19 as primary diagnosis		1.01	*(0.97, 1.04)*

Table 5: The impact of patient enrolment rates on in-hospital mortality and length of stay under different modelling assumptions.

Scenario	**Odds ratio associated with in-hospital mortality for every 10% increase in enrolment *(95% confidence interval)***		**Relative change in length of stay for every 10% increase in enrolment *(95% confidence interval)***	
Baseline	0.97	*(0.92, 1.03)*	1.8%	*(-1.2%, 4.9%)*
Weighting used to create enrolment variable (applied to both age bands)				
w_0 = 60%, w_1 = 40%, w_2 = 0%	0.96	*(0.91, 1.02)*	1.7%	*(-1.4%, 4.9%)*
w_0 = 100%, w_1 = 0%, w_2 = 0%	0.98	*(0.93, 1.02)*	1.2%	*(-1.3%, 3.7%)*
w_0 = 0%, w_1 = 100%, w_2 = 0%	0.95	*(0.90, 1.01)*	0.9%	*(-1.7%, 3.6%)*
w_0 = 50%, w_1 = 50%, w_2 = 0%	0.96	*(0.90, 1.02)*	1.7%	*(-1.4%, 5.0%)*
w_0 = 60%, w_1 = 30%, w_2 = 10%	0.96	*(0.91, 1.02)*	2.1%	*(-1.1%, 5.4%)*

Exclude patients with suspected COVID-19 as primary diagnosis	0.98	*(0.92, 1.04)*	0.2%	*(-2.8%, 3.3%)*

Workstream 1 – Detailed methods for CVW analysis

Data sources

The data sets used in this analysis are provided in Table 6.

Table 6. Data sets used in analysis

Data	Source	Data description	Dates used
HES APC[13]	NHS Digital	Pseudonymised national (England) hospital admissions dataset	August 2018 to end July 2021
CVW start dates	Kent, Surrey and Sussex Academic Health Science Network (KSS AHSN)	Start dates of the CVW service in each of 128 English NHS acute or specialist hospital trusts	Final date 22 February 2021
Index of Multiple Deprivation, 2019 (IMD 2019)[14]	UK Ministry of Housing, Communities & Local Government	Small area-level national (England) deprivation index	2019 index version
Acute beds occupied by COVID-19 patients[15]	NHS England and Improvement	Hospital trust-level data published weekly on the proportion of acute beds occupied by COVID-19 patients	March 2020 to end February 2021

Setting and participants

From HES APC data, we extracted information on all individuals discharged alive from 123 English hospital trusts where there had been a confirmed or suspected COVID-19 ICD-10 diagnosis code (U071 or U072) recorded as a primary diagnosis at any point during the inpatient stay. We included all patients discharged between 17 August 2020 and 28 February 2021, a period covering the beginning, the peak, and the start of the decline of England's second COVID-19 wave.[16] Where a patient had two or more relevant inpatient stays, all stays were included in our analysis. The 123 acute trusts were selected from the KSS AHSN list of 128, having excluded four specialist trusts (not expected to treat patients with COVID-19 as a primary cause of the admission), and one non-specialist acute trust whose CVW start date was not known. We additionally extracted limited data on numbers of similar COVID-19 discharges for all trusts in the HES APC data, to compare the number in our analysis with national counts of similar patients.

Analytical approach

We developed multivariate models to examine the impact of the availability of CVW (the primary independent variable of interest) on two outcomes: the LOS of the COVID-19 inpatient stay, and on subsequent readmissions for COVID-19.

Variables

In our analyses we included a range of factors likely to be associated with LOS and rates of readmissions for COVID-19 patients;[17-22] see Table 7. Time period categories were included to take account of fluctuating baseline LOS and rates of readmissions over the analysis period.[23] The proportion of beds occupied by COVID-19 patients was included to represent COVID-related bed pressures.

Table 7. Factors included in models

Modelling Factors	Categories assigned to each COVID-19 patient discharge
Age at admission	0-17, 18-49, 50-64, 65-79, 80s+
Gender	Male, Female
Ethnic group	Asian, Black, White, Mixed, Other, Unknown
Charlson comorbidity index category [24]	0, 1, 2, 3, 4, 5, 6+
Whether the stay was the person's first COVID-19 hospital stay	Yes, No
Whether the inpatient stay was an emergency admission	Yes, No (elective)
Deprivation quintile IMD (2019)	1 – most deprived to 5 – least deprived, with a sixth category for unknown area
Time period of the discharge date	14 categories, each covering a 14-day period starting from 17 August 2020
Proportion of all acute beds occupied by COVID-19 patients	A trust- and week-specific continuous measure (mapped to week of discharge)

Age, gender, ethnic group, hospital trust, emergency admission information, time period of discharge were all taken from information recorded against the inpatient COVID-19 stay itself, as was the lower super output area (LSOA) of residence of the patient, which was used to add the deprivation quintile. The Charlson comorbidity category index score [24] was calculated using HES APC data (specifically, diagnostic information) from two years (730 days) prior to the COVID-19 admission date. The proportion of acute beds occupied by COVID-19 patients was assigned to the appropriate week of the date of discharge.

From the COVID-19 inpatient stay, we recorded the LOS as the discharge date minus the admission date. In our analyses, we replaced all LOS of greater than 60 days with 60 days to reduce the potentially distorting impact of very long LOS.

Using subsequent HES APC data, we recorded the occurrence of any readmission for COVID-19, to any hospital, within 28 days of the COVID-19 stay discharge date. Here we included any confirmed or suspected COVID-19 ICD-10 diagnosis code, recorded as either a primary or secondary diagnosis on the admission episode of the inpatient stay.

The variable indicating the availability of CVW was assigned depending on the hospital trust and date: for any individual trust, every discharge from the day of the CVW service start date onwards was assigned as having a CVW available, while all discharges before that date were assigned to having no CVW available. Where a trust was known to have not implemented a CVW by the end of the analysis period, all that trust's discharges were assigned as having no CVW available.

Statistical analysis

Basic descriptive statistics were initially used to provide information on the characteristics of all patients included in the analysis, and also split into two mutually exclusive groups: COVID-19 patients discharged from a hospital trust where a CVW was, and was not, available. We compared differences between the groups using Pearson's chi-squared test for categorical variables and a two sample t-test for one continuous variable.

We calculated unadjusted means of COVID-19 LOS and rates of COVID-19 readmission for all categories of patient characteristics. Negative binomial regression was used to examine the relationship between independent variables and LOS,[10] and logistic regression was similarly used for readmissions. To account for clustering at the level of the hospital trust, GEE approaches were used.

To investigate the robustness of our findings, we carried out a number of sensitivity analyses. For both outcomes, we tested two alternatives for the time period of discharge variable: seven days and 28 days, and also tested including data from England's first COVID-19 wave (specifically from 2 March 2020). We also tested two further LOS outcomes: one untrimmed at 60 days (that is, the crude LOS, however long), and another where we disregarded episodes of care at the beginning of the inpatient stay, where these appeared to

predate the COVID-19 diagnosis. Moreover, we iteratively examined the statistical significance of each independent variable as well as the impact of their order, by constructing our models step-by-step.

All analyses were carried out in SAS version 9.4 (SAS Institute, North Carolina, US).[11]

Ethical considerations

The use of HES APC data was governed by a data sharing agreement with NHS Digital covering NIHR RSET analysis (DARS-NIC-194629-S4F9X). A protocol covering this analysis (as one part of a wider study) received ethical approval from the University of Birmingham Humanities and Social Sciences Ethics Committee (ERN_13-1085AP39) and was categorised as a service evaluation by the HRA decision tool and UCL/UCLH Joint Research Office (Jan 2021).

Work stream 3 and 4 - Detailed methods for i) national study of implementation and patient/staff experiences, and ii) case-studies of implementation, patient/staff experiences.

NATIONAL STUDY OF IMPLEMENTATION AND PATIENT/STAFF EXPERIENCES

The aim of the national study of implementation and patient/staff experiences was to: a) understand the development of COVID-19 remote home monitoring services, and b) analyse the implementation of COVID-19 remote home monitoring services, and patient and staff experiences of care in sites across England.

This aspect of the study included data from: a) national staff and patient or carer surveys, and b) interviews with national leaders and documentary analysis of COVID-19 remote home monitoring services.

National surveys (staff and patients)

Sample and recruitment

Selection of sites

Twenty-eight services were included in our national evaluation. Each site had a research lead (MS, CVP, HW, JB, IL, LH) to support data collection and act as an ongoing point of contact for the site.

To obtain maximum variation, we sampled services based on a range of criteria, including the setting (primary care or secondary care), type of model (pre-hospital, early discharge, both), mechanism for patient monitoring (paper-based, app, both), geographic location (across different areas of the country), timing of implementation (implemented since wave 1 of the pandemic or recently implemented) and involvement in the evaluation with the other evaluation partners (Imperial and IAU).

Sites were recruited through an expression of interest process whereby we presented our study at local and national meetings and asked sites to express interest in participating. Clinical Research Networks facilitated the setup of sites and local governance approvals. Some sites were identified through our Phase 1 evaluation.

Staff survey

We conducted a survey of staff involved in delivering COVID-19 remote home monitoring services in the 28 services, including clinical leads, delivery staff and data staff.

Staff at participating sites distributed surveys to staff. All survey sites were asked to keep a record of the number of surveys they have sent out to determine staff response rates.

For the staff survey, staff received an email from their GP practice/hospital or other relevant networks (together with reminder emails) with a link to fill out an online survey.

Patient survey

Twenty five of the 28 sites agreed to conduct the patient and carer survey. To participate in our survey, participants needed to be:

I. 18 or over,
II. Proficient in English (or one of the following languages: Polish, Bengali, Urdu, Punjabi, French and Portuguese),
III. Eligible to receive COVID-19 remote home monitoring services, and must also have been offered and received COVID-19 remote home monitoring.

National and local eligibility for COVID-19 remote home monitoring varies. We were flexible within our sampling to take into account both national and local eligibility criteria. For reference, the national eligibility guidelines are as follows: To be eligible for receiving COVID-19 remote home monitoring patients must have a confirmed or suspected diagnosis of COVID-19 plus be one of the following: (a) symptomatic with COVID-19 and aged 65 years or older, b) symptomatic with COVID-19 and under 65 years but 'clinically extremely vulnerable' (using the clinically extremely vulnerable to COVID list) to COVID.[25]

For the patient survey, NHS staff from participating services sent the patient survey to patients (or their carers if applicable) onboarded on to the service between 1st January 2021 and11th June 2021. NHS sites decided how to best disseminate the survey to their patients (either via post or text/email). All survey sites were asked to keep a record of the number of surveys they have sent out to determine patient response rates.

If patients were not able/willing to take part in the survey, they were given the option to ask their carer or family member to complete the survey on their behalf, reflecting on the patient's experience with the service. The survey was sent to patients who have received care at participating sites by NHS staff. Patients/carers returned completed surveys directly to the study team for analysis, either electronically through REDCap or via post using pre-paid envelopes. In addition to English, we also offered participants the opportunity to receive an information sheet and survey in six other languages (Polish, Bengali, Urdu, Punjabi, French and Portuguese).

Measures

Staff survey

We developed staff surveys specifically for this study.

Different sets of questions were developed for different groups of staff (i.e. one survey for service leads and one survey for staff delivering the service). The main purpose of the staff survey was to gather information on the staff involved in delivering COVID-19 remote home monitoring services, different set-up processes and models implemented, staff experiences of implementing these models, factors influencing delivery and staff perceptions of patient engagement with the service. As part of the survey, we also sought to explore different experiences of analogue versus tech-enabled models. The survey included a number of closed questions which focused on documenting staff experiences of setting up, managing and delivering the service. These questions were followed by a single, open text question at the end to give staff the opportunity to share any wider thoughts. To reduce burden and maximise response rates, the online survey was developed to take no longer than 15-20 minutes to complete. The survey was delivered using an online platform (REDCap).

Survey questions were reviewed, and sense-checked by our Clinical Advisory Group, PPI group and our cohort of 70@70 nurses (senior nurse and midwife clinical leaders with demonstrable experience of building a research-led care environment for patients). The theoretical frameworks were used as a sensitising device to inform the development of questions in the surveys and interviews. The staff survey was piloted with a small number of sites. Piloting aimed to determine whether questions were appropriate and relevant, while identifying areas for further refinement prior to circulation nationally. In response to feedback, we amended some of the staff survey questions and response option wording to improve clarity, added response options, re-ordered questions and amended question format.

Patient survey

We developed patient surveys specifically for this study.

The aim of the patient survey was to capture the experiences of patients who received COVID-19 remote home monitoring, and their engagement with the COVID-19 remote home monitoring service. We developed a patient experience survey for this purpose. The survey included closed questions focused on: the service that patients have received, their experience with the service and their engagement with the service. As part of the survey, we also asked questions about patients experience of analogue versus tech-enabled models. These questions were followed by a single open text question at the end to give participants the opportunity to share any wider thoughts. Survey and interview questions were informed by relevant service documentation,[7, 25] theoretical frameworks relating to social, political and technical contexts [26-29] and behaviour,[30] and previous literature on engagement.[31, 32] We also included a section at the end of the survey to ask about participants' socio-demographic characteristics (including questions on gender, age, ethnicity, education, employment, disability, sexuality, first language and geographical region). Questions on demographic characteristics were informed by previous literature.[33-37] To reduce burden and maximise response rates, the patient survey was designed to take between 15 and 30 minutes to complete. The survey was delivered using the online platform REDCap.

Survey questions were reviewed, and sense-checked by our Clinical Advisory Group, PPI group and our cohort of 70@70 nurses. The theoretical frameworks were used as a sensitising device to inform the development of questions in the surveys and interviews. The patient survey was piloted with our PPI group and some members of the public. In response to feedback for the patient survey, and to make the survey more accessible, we amended some of the questions, increased the font size, reduced the number of questions and added definitions for key terms (such as oximeter).

Data collection

Staff survey

For the staff survey, staff were asked to follow an online link to complete the survey. If they followed the link, they reached an information page which provided background to the study, potential risks and a description of how the data will be used to ensure informed and voluntary participation. It was emphasised that individual responses would be treated confidentially and reported anonymously. Staff were asked to tick a box to indicate their consent to take part in the study. Data collection took place between February and May 2021.

Patient survey

For the patient survey, patients were approached by NHS staff to take part in a survey in one of two different ways: 1) if the patient was monitored through the use of an app, they received an SMS/email with a link to the online survey, 2) if the patient was monitored through regular phone calls and a paper-based recording method, they received the survey in the post (with a pre-paid addressed envelope). Whilst most surveys were distributed at discharge, some sites chose to distribute the paper survey at onboarding and then remind patients at discharge to complete the survey. NHS staff distributed the online and paper version of the survey so the research team had no access to patient information. Both survey options (online and paper) included prefacing information with a background to the study, potential risks, indicating voluntary participation, anonymity and a description of how the data will be used. This page also included boxes that patients/carers were asked to tick to indicate their consent to take part in the study. The method of administering the survey to patients (i.e. NHS staff sending to patients) meant that there were no reminders. Due to

research capacity, we were unable to conduct the survey with patients over the phone. Data collection took place between March and June 2021.

Data management

Surveys were returned to the research team, either electronically through REDCap (staff and patient surveys), or by posting completed surveys in pre-paid envelopes to our RSET team members at the Nuffield Trust or UCL (patient surveys only). Surveys received via post were stored securely in locked filing cabinets within secure Nuffield Trust or UCL offices. Data from patient surveys sent via post were inputted into REDCap by members of the research team. Data from the patient surveys were directly stored in the UCL Data Safe Haven via REDCap, as this will include identifiable information (e.g. postcode data). Data from the completed surveys were stored securely using password protected spreadsheets to which only the RSET and BRACE researchers had access to.

Analysis

Sites were characterised with respect to their population size, the proportion in urban versus rural areas, and the proportion in the most and least deprived areas (with respect to national quintiles). For sites based on CCG areas we calculated these characteristics using publicly available data at (LSOA) level mapped to CCGs, while for trust-based sites we used data derived from inpatient HES admissions during the financial year 2019/20, in addition to web searches for the trust catchment populations.

The quantitative survey data were analysed using SPSS (version 25). Descriptive statistics, multivariate and univariate analyses were conducted to compare staff experiences of delivering the service across staff groups and service models, and patient experiences of the service across patient groups and service models (as reported by patients and carers). We offered to carry out site-specific analyses of patient experience data for participating sites.

National lead interviews and documentary analysis

Sample and recruitment

To understand the development of the national programme and capture changes in design and implementation over time, we conducted interviews with national leaders (n=5) and analysed key documents. National leaders (working on the development and supporting implementation of COVID-19 remote home monitoring services) were sampled purposively to capture the views of key leaders with different roles across organisations (i.e. NHSE/I, NHS Digital, NHSX, etc.). The documentary analysis included documents developed at a national scale, including SOPs and other guidance for sites.

National leads were contacted via email and asked if they would like to take part. If happy to take part, they were asked to give their consent in advance of the interview. Researchers then arranged a convenient time for the interview.

Measures

We developed a topic guide for national lead interviews. The topic guide included questions about how the service originated, how the service was implemented in wave 1 of the pandemic, adaptations since wave 1 of the pandemic, how the service became a national programme, the leadership and governance arrangements of the service, the aims and objectives of the service, expected outcomes, resources, technology, data, patient experience, strengths and limitations, and lessons learned.

Data collection

National lead interviews were conducted by four researchers (MS, CV, HW, NJF). Three of the interviews were conducted by one researcher and two interviews were conducted by a pair of researchers. Interviews were carried out via telephone or an online platform (e.g. Zoom or MS Teams) as preferred by the participant. Data collection took place between February and May 2021.

Analysis

For national lead interviews, data collection and analysis were carried out in parallel and facilitated through the use of RAP sheets as explained in Vindrola-Padros *et al*. [38] RAP sheets were developed per site to facilitate cross-case comparisons and per population (to make comparisons between sub-groups). The categories used in the RAP sheets were based on the questions included in the interview topic guide, maintaining flexibility to add categories as the study is ongoing.

CASE STUDIES OF IMPLEMENTATION, STAFF AND PATIENT EXPERIENCES

The aim was to document the implementation of COVID-19 remote home monitoring services (including the identification of factors acting as barriers and enablers in implementation), staff experiences of delivering the service and in-depth patient experiences of care in a sample of 17 sites. All 17 sites also took part in the staff survey and 15/17 sites took part in the patient survey.

This aspect of the study included data from: a) interviews with staff and b) interviews with patients/carers.

Sample and recruitment

Site selection

A smaller sample of the overall study sites were included as case studies in order to conduct a more in-depth analysis of implementation, patient and staff experiences.

Seventeen of the 28 sites were selected as in-depth case study sites using the aforementioned criteria (see national site selection). Four of the 17 sites were purposively selected by NHSX for a more in-depth analysis of implementation and patient and staff experiences of tech-enabled models of care; sites using different tech-enabled platforms were selected.

Staff interviews

For staff interviews, we aimed to purposively sample one or two members of staff delivering the service, one staff member leading the service (operationally or clinically), and one staff member knowledgeable about service data collection/analysis at each of the 17 sites (note, one staff member may fulfil more than one role).

Participants for the staff interviews were approached through each case study site's contact person/gatekeeper. Potential interviewees were introduced to the researcher or asked to contact the researcher to take part. The researcher contacted these potential participants via email and sent them a participant information sheet. Participants were given 48 hours to review the information and ask questions about the study. If the participant agreed to take part in the study, they were asked to sign the consent form. An informed consent process using participant information sheets and written consent (scanned forms or typewritten/electronic signature) was used for recruitment to ensure informed and voluntary participation.

Patient interviews

We aimed to interview up to six participants (patients or their carer) who had received, disengaged or declined with COVID-19 remote home monitoring from each site. To participate in our patient or

carer interviews, participants needed to be 18 or over, proficient in English (or one of the following languages: Polish, Bengali, Urdu, Punjabi, French and Portuguese), eligible to receive COVID-19 remote home monitoring services, and must also have been offered and either received or refused the service. If patients were not able/willing to take part in the interview, patients were asked by site coordinators if their carer (if they have one) could be approached to capture their perceptions of the patient's journey and overall experience with the service.

We asked the main contact person at each site (the study coordinator), to identify a convenience sample of four to six patients (or their carers). To identify potential participants, the study coordinator contacted potential participants to see if they were happy to be approached by a researcher. If they agreed, the researcher contacted the patient or their carer via telephone or email to discuss the study. NHS staff identified patients on behalf of the study team using a purposive sampling approach. To be inclusive and capture a wide range of views, we asked sites to select patients with different characteristics (e.g. age, gender, ethnicity, deprivation score (by postcode), employment status, and comorbidities). We also asked sites to identify interviewees who had declined or disengaged from the service and those who used different data submission methods (if applicable).

If the patient or their carer was contacted via phone, they were asked if a participant information sheet and consent form can be sent via email. If they preferred post, both of these documents were sent via post with a pre-paid addressed envelope so they could return the signed consent form to the team. If the patient was contacted via email, the participant information sheet and consent form were sent in a subsequent email and the patient was given the option to schedule a call with the researcher to discuss the study. The participant information sheet contained information on the study, potential risks and a description of how the data will be used to ensure informed and voluntary participation. If the patient or their carer agreed to take part in the study, they were asked to email back the signed consent form (scanned forms or typewritten/electronic signature). If patients were not able/willing to take part in the interview, we asked patients if we can approach their carer (if they have one) to capture their perceptions of the patient's journey and overall experience with the service.

Measures

Staff interviews

Staff interview topic guides included questions for staff leading a service, staff delivering a service and staff involved in data. The staff topic guides included questions about their role, the origin of the model, the aims and goals of the model, resources and processes of the model, staff training, facilitators and barriers of implementation, patient engagement, adaptations, monitoring and evaluation, impact, and recommendations and sustainability.

In the four sites for in-depth analysis of tech-enabled platforms, interviews with delivery staff were extended to include a 'think aloud' section where staff narrate the process of using the platform in situ (think aloud methodology [39]).

Patient and carer interviews

Patient and carer interview topic guides included questions for patients who had received COVID-19 remote home monitoring services, those who had declined to receive the service and those who disengaged from the service. The interviews with patients and carers focused on documenting their journeys of remote home monitoring, their experiences of being ill and monitored at home, experiences with escalation and discharge, their engagement with the service, and

recommendations for improving these models. Interview questions (as with survey questions) were informed by relevant service documentation [7, 25] and literature.[26-32]

During the interview, we asked patients/carers some brief questions relating to socio-demographic characteristics including whether they are a patient or carer, age, gender, ethnicity, how many people they live with, education and qualifications, employment status, English as a first language, disability and postcode (the latter to be used as indicator of social deprivation).[33-37] We emphasised that as with all parts of the interview, these questions are optional.

We intended to conduct 'think alouds' with patients who had used tech-enabled data submission from the four sites selected for in-depth analysis of tech-enabled platforms. However, patients did not have access to the platforms after discharge and recall of the use of these platforms during their illness was poor. Consequently, 'think aloud' methodology was discontinued for patient interviews.

To determine whether questions were appropriate and relevant, we discussed the interview topic guides with our PPI members and the 70@70 nurses. The topic guides were amended accordingly.

Data collection

The researcher arranged a time to carry out the interview. Each site had a different lead researcher who conducted the interviews and liaised with sites on an ongoing basis. Interviews were conducted by six researchers (MS, CV, HW, LH, IL, JB). Interviews were carried out via telephone or an online platform (e.g. Zoom or MS Teams) as preferred by the participant. Data collection for interviews was conducted between February and June 2021.

Data management

All interviews were semi-structured, audio recorded (subject to consent being given), transcribed verbatim by a professional transcription service (TP Transcription Limited), anonymised and kept in compliance with the General Data Protection Regulation (GDPR) 2018 and Data Protection Act 2018.

Analysis

For staff and patient interviews, data collection and analysis were carried out in parallel and facilitated through the use of RAP sheets as explained in Vindrola-Padros *et al*. [38] RAP sheets were developed per site to facilitate cross-case comparisons and per population (to make comparisons between sub-groups). The categories used in the RAP sheets were based on the questions included in the interview topic guide, maintaining flexibility to add categories as the study is ongoing. Further details on analysis methods for each chapter are provided elsewhere (see *Chapter 4* and *8-11*).

Supplementary file 1 – References

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