Sensor-based surveillance for digitising real-time COVID-19 tracking in the USA (DETECT): a multivariable, population-based, modelling study

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Summary

Background Traditional viral illness surveillance relies on in-person clinical or laboratory data, paper-based data collection, and outdated technology for data transfer and aggregation. We aimed to assess whether continuous sensor data can provide an early warning signal for COVID-19 activity as individual physiological and behavioural changes might precede symptom onset, care seeking, and diagnostic testing.

Methods This multivariable, population-based, modelling study recruited adult (aged ≥18 years) participants living in the USA who had a smartwatch or fitness tracker on any device that connected to Apple HealthKit or Google Fit and had joined the DETECT study by downloading the MyDataHelps app. In the model development cohort, we included people who had participated in DETECT between April 1, 2020, and Jan 14, 2022. In the validation cohort, we included individuals who had participated between Jan 15 and Feb 15, 2022. When a participant joins DETECT, they fill out an intake survey of demographic information, including their ZIP code (postal code), and surveys on symptoms, symptom onset, and viral illness test dates and results, if they become unwell. When a participant connects their device, historical sensor data are collected, if available. Sensor data continue to be collected unless a participant withdraws from the study. Using sensor data, we collected each participant's daily resting heart rate and step count during the entire study period and identified anomalous sensor days, in which resting heart rate was higher than, and step count was lower than, a specified threshold calculated for each individual by use of their baseline data. The proportion of users with anomalous data each day was used to create a 7-day moving average. For the main cohort, a negative binomial model predicting 7-day moving averages for COVID-19 case counts, as reported by the Centers for Disease Control and Prevention (CDC), in real time, 6 days in the future, and 12 days in the future in the USA and California was fitted with CDC-reported data from 3 days before alone (H_0) or in combination with anomalous sensor data (H_1). We compared the predictions with Pearson correlation. We then validated the model in the validation cohort.

Findings Between April 1, 2020, and Jan 14, 2022, 35 842 participants enrolled in DETECT, of whom 4006 in California and 28 527 in the USA were included in our main cohort. The H_1 model significantly outperformed the H_0 model in predicting the 7-day moving average COVID-19 case counts in California and the USA. For example, Pearson correlation coefficients for predictions 12 days in the future increased by 32·9% in California (from 0·70 [95% CI 0·65–0·73] to 0·93 [0·92–0·94]) and by 12·2% (from 0·82 [0·79–0·84] to 0·92 [0·91–0·93]) in the USA from the H_0 model to the H_1 model. Our validation model also showed significant correlations for predictions in real time, 6 days in the future, and 12 days in the future.

Interpretation Our study showed that passively collected sensor data from consenting participants can provide real-time disease tracking and forecasting. With a growing population of wearable technology users, these sensor data could be integrated into viral surveillance programmes.

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Introduction

In the USA, approximately 70 million individuals wear a smartwatch or fitness tracker.[1] Sensors can be used to measure an individual's unique physiological and behavioural baseline, deviations from which might indicate the early onset of viral infections, such as COVID-19.[2–6] Relying on clinic visits and laboratory test results, traditional surveillance of a viral illness is often delayed in the cascade of someone feeling ill, seeking care, getting tested, and finally receiving their diagnostic test results, which must be reported to, and aggregated by, a local and then national public health organisation. Surveillance data collection is further delayed by reliance on outdated technologies, such as the fax machine,[7] to

Research in context

Evidence before this study

We searched PubMed for articles published in English between Jan 1, 2020, and March 25, 2022, using combinations of words or terms that included "viral illness" OR "COVID-19" AND "sensors" OR "smartwatch" OR "fitness tracker". There is a growing body of evidence that wearable sensors can identify physiological and behavioural changes relative to a person's healthy baseline that are associated with a viral infection. These changes in sensor data can be identified before symptom onset and during acute illness, and recovery back to baseline can be monitored. Previous research has shown that population-level deviations in sensor data could be used to predict real-time influenza-like illness and SARS-CoV-2 infection. Sensor data had yet to be applied to long-term COVID-19 tracking and forecasting or incorporated into an autoregressive model that also considers data from traditional surveillance sources.

Added value of this study

This study used nearly 2 years of sensor data during the COVID-19 pandemic to examine whether the proportion of participants with anomalous sensor data could be used to predict COVID-19 cases in real time and in the future. We found that sensor data (alone or with Centers for Disease Control and Prevention data) provided real-time and forecasting predictions of COVID-19 activity that were on a par with the lead time and correlations provided by wastewater surveillance.

Implications of all the available evidence

This study adds to the growing evidence that sensors can be used for alerting the individual of potential viral illness and for population-based surveillance. Sensor-based surveillance of viral illness should be integrated into public health programmes to identify viral illness in the individual and in the population.

transmit case data to public health organisations following the manual entry of data, which can introduce potential errors and cause additional delay. Sensors, such as smartwatches and fitness trackers, can collect continuous physiological and behavioural data across a large population of users that can be sent in a raw, anonymised, or aggregated form to a central database in near real time, digitising and speeding up the process of disease surveillance.

Several novel data sources for surveying viral illness have shown promise for tracking viral activity in near real time. Wastewater surveillance data have provided good predictors of SARS-CoV-2 activity;[8] however, wastewater surveillance requires routine, active collection and testing from many sites across different geographical areas, with associated costs and delays. In addition, estimates of viral activity in wastewater can be impacted by catchment area, wastewater flow rates, and other confounding factors. Google search terms have shown promise in tracking influenza-like illness in real time, but are affected by media coverage, causing overestimations during epidemic periods.[9] Symptom reporting tools, such as Flu Near You (now Outbreaks Near Me),[10] smart thermometers,[11,12] and symptom tracking apps can provide real-time symptom data, but require continued input from users and are subject to bias towards increased reporting when people are ill, as well as user fatigue over time.

Previous work has shown that aggregated sensor data can be used to improve real-time detection of influenza-like illness in US states.[13] One study found that sensor data anomalies were correlated with COVID-19 case data during a short time period in the early stages of the pandemic, but did not assess autoregressive models incorporating traditional surveillance or examine long-term COVID-19 tracking or future predictions.[14] Digital Engagement and Tracking for Early Control and Treatment (DETECT) is an app-based research study that allows participants to prospectively share sensor and survey data related to viral infections to better understand individual responses to viral infections and track viral illness in a population. Previous research under DETECT has shown that sensor data can improve our ability to distinguish COVID-19 from other viral illnesses,[2,6] track long-term physiological and behavioural recovery from COVID-19,[15] and track physiological responses to COVID-19 vaccines.[16]

Creating a passive surveillance system that only requires volunteers to wear a smartwatch or fitness tracker to participate could provide a valuable data stream to supplement other novel and traditional surveillance platforms. Wearable data could help to predict viral illness trends in a population, as physiological changes from baseline might even precede symptoms.[8] Due to the frequent and increasing use of sensors with the ability for ongoing, passive data collection in the USA and worldwide, sensors can also potentially provide geographically specific data on community outbreaks. Here, we aimed to explore whether sensor data collected for the DETECT study can be used to track and provide an early indicator of COVID-19 activity in California specifically and in the USA generally.

Methods

Study design and participants

The DETECT study was launched on March 25, 2020, and is open to any adult (aged ≥18 years) living in the USA or Australia who has a smartwatch or fitness tracker on any device that connects to Apple HealthKit or Google Fit (eg, Fitbit). Participants join the study by downloading the MyDataHelps app, which is available on Android and iPhone operating systems, and completing an electronic informed consent form. For this specific multivariable, population-based, modelling study, we included individuals in the USA who participated in DETECT

between April 1, 2020, and Jan 14, 2022, in the main model development cohort and included individuals in the USA who participated in DETECT between Jan 15 and Feb 15, 2022, in the validation cohort. Our initial recruitment efforts involved outreach from several partners, including posting a link to our study on the Fitbit app (appendix p 2). Individuals with less than 30 total resting heart rate measurements were excluded from our analysis because we wanted to ensure that we had enough data to calculate their unique baseline.

The security and privacy of our participants was considered at multiple levels. The technology platform, which was leveraged to collect participant data through an app-based experience, conforms to National Institute of Standards and Technology 800-53 (revision 4) requirements at a moderate level for availability, security, and privacy. Data storage is hosted within Amazon's US-based Amazon Web Services cloud platform in compliance with the Health Insurance Portability and Accountability Act and the Federal Risk and Authorization Management Program. Secure transfer protocols were used to access data by authorised individuals and analyses were done on data that had been stripped of major identifiers. Data visualisations incorporated in the user experience and user interface provide transparency in terms of what data (eg, electronic health record and device data) the participants are sharing. Privacy and security measures employed by the study were detailed during the informed consent process and participants had the option to pause or stop data sharing or withdraw from the study at any time.

The protocol for this study was reviewed and approved by the Scripps Office for the Protection of Research Subjects (institutional review board 20-7531), and can be found online.

Procedures

Once a participant joins DETECT, they fill out an intake survey of demographic information, including their ZIP code (postal code), and surveys on symptoms, symptom onset, and viral illness (influenza and COVID-19) test dates and results, if they become unwell. Participants can also enter COVID-19 vaccine types and vaccination dates and have the option to connect and share their electronic health record data. When a participant joins DETECT and connects their device, historical sensor data (eg, resting heart rate and step count) are collected, if available. Survey data on tests, symptoms, and vaccination that occurred before joining the study can also be entered. Sensor data continue to be collected unless a participant withdraws from the study. Sleep data were collected from some participants but were not used for this study.

Modelling and statistical analysis

Using sensor data, we identified each participant's mean (SD) daily resting heart rate and step count during the entire study period (April 1, 2020–Jan 14, 2022). Days with missing resting heart rate measurements or step counts were not considered as they probably indicated a low wear time. For each user, a daily Z score was calculated for resting heart rate by subtracting mean resting heart rate for the total study period from daily resting heart rate and dividing the total by the SD of resting heart rate for the entire study period. A daily Z score was also calculated for step count for each user by use of the same equation, substituting heart rate for step count.

See Online for appendix

To identify whether there were differences in physiological response by variant, we analysed changes in Z scores for resting heart rate and step count in COVID-19-positive, symptomatic individuals by pandemic wave (Jan 1, 2020–Nov 30, 2021 for wave 1; Dec 1, 2021–Jan 15, 2022 for wave 2); we only considered symptomatic individuals who had submitted a symptom onset date for this analysis.

For the main analysis, we used two thresholds to identify anomalous data. For threshold 1, days were identified as anomalous if an individual had a daily Z score for resting heart rate of more than 2 and a daily Z score for step count of less than –1. For threshold 2, days were identified as anomalous if an individual had a daily Z score for resting heart rate of more than 0·75 and a daily Z score for step count of less than –1. Threshold 2 used the mean maximum deviation in Z scores for COVID-19-positive participants identified by earlier studies.[17,18] 7-day moving averages of the proportion of daily users with anomalous sensor data were compared with 7-day moving averages of COVID-19 case counts in California and the USA, as reported by the Centers for Disease Control and Prevention (CDC),[19] by use of Pearson correlation. Comparisons were made in matched time and a lead

For the **protocol** see https://clinicaltrials.gov/ct2/show/NCT04336020

	California (n=4006)	USA (n=28 527)
Number of measurement days*	1 647 324	11 888 728
Fitbit users	3877 (96·8%)	27 961 (98·0%)
Apple HealthKit	129 (3·2%)	566 (2·0%)
Sex		
Female	2342/4004 (58·5%)	17 548/27 668 (63·4%)
Male	1641/4004 (41·0%)	10 004/27 668 (36·2%)
Other	21/4004 (0·5%)	116/27 668 (0·4%)
Age group		
18–39 years	1138/4002 (28·4%)	8002/27 664 (28·9%)
40–64 years	2052/4002 (51·3%)	14 929/27 664 (54·0%)
≥65 years	812/4002 (20·3%)	4733/27 664 (17·1%)
COVID-19 swab test results†		
Positive	248/4018 (6·2%)	1885/21 933 (8·6%)
Negative	3770/4018 (93·8%)	20 048/21 933 (91·4%)

Data are n, n (%), or n/N (%). Denominators vary due to missing data or multiple counts per individual. *Days when users had both resting heart rate and step count measurements. †Multiple tests might be reported for the same individuals.

Table 1: **Characteristics of the model development cohort (data from April 1, 2020, to Jan 14, 2022)**

time of 1–12 days. We also used Pearson correlation to compare the number of people with self-reported COVID-19 in the DETECT study with the number of CDC-reported COVID-19 cases in the USA in matched time and a lead time of 1–12 days.

A negative binomial model was used to predict the CDC-reported 7-day moving average of COVID-19 case counts for the state of California and the entire USA in real time, 6 days in the future, and 12 days in the future. Threshold 1 was used for the modelling as this threshold showed higher correlations with the 7-day moving averages of CDC-reported COVID-19 cases than did threshold 2. We fit the baseline H_0 model with CDC data from 3 days before the current time period. The H_{naive} model used only sensor data—the 7-day moving average of the proportion of users with anomalous data (x_j) for each day j—to predict the CDC-reported 7-day moving average of COVID-19 cases, with offset n_j. The offset, n_j, was a constant and represented the population size in California or the USA. To create the H_1 model, a 3-day lagged autoregressive term y_{j-3} was added to the H_{naive} model, in which the CDC-reported 7-day moving average of COVID-19 cases is defined as y for each day (j). The j–3 in this autoregressive term represents the typical reporting lag from the CDC. The negative binomial model, H_1, with offset term $\log(n_j)$ was

$$H_1: \log_e(y_j)=\beta_0+\beta_y\times y_{j-3}+\beta_x\times x_j+\log_e(n_j)$$

This model was based on previous modelling work predicting influenza-like illness by use of sensor data.[13]

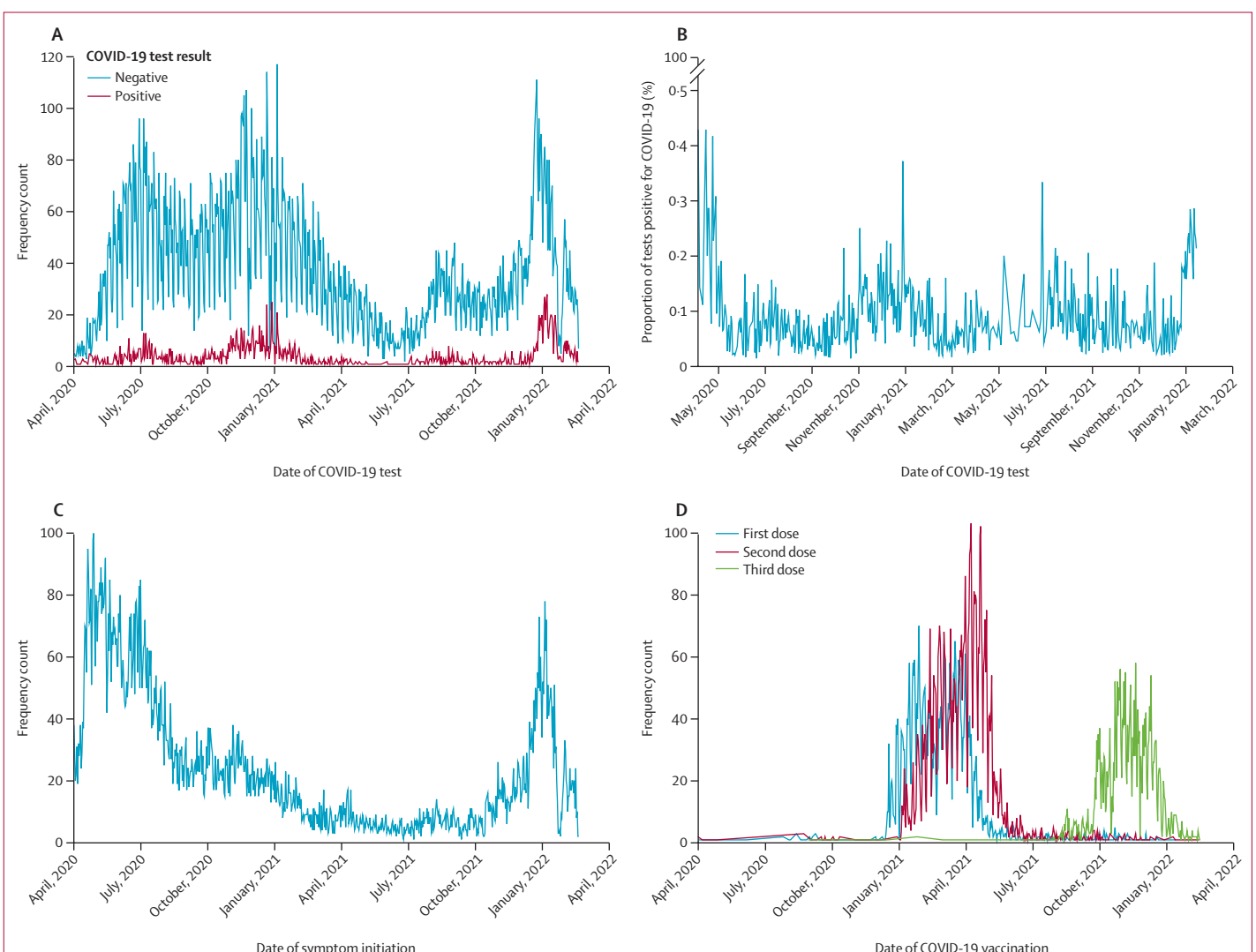

Figure 1: **COVID-19 incidence, symptoms, and vaccination**
(A) Count of COVID-19 test results by date, with multiple tests per person not excluded. (B) The proportion of tests that were positive for COVID-19 by date, with multiple tests per person not excluded. (C) Count of self-reported symptom initiation by date. (D) COVID-19 vaccination counts by date.

As in our previous study,[13] the H_1 model assumed that the 7-day moving average of COVID-19 cases (y_i) was affected by the proportion of users with anomalous data, whereas the baseline model (H_0) did not, omitting x_i such that the null hypothesis was H_0:β_x=0. We compared the predicted 7-day moving averages of COVID-19 cases for each of the three models with the CDC-reported ones using Pearson correlation. After fitting the full model, we then validated the model using data from Jan 15 to Feb 15, 2022, to predict the 7-day moving averages of COVID-19 cases in real time, 6 days in the future, and 12 days in the future in the USA and California.

SAS (version 9.4) was used for all analyses. Tableau (version 2021.1.10) was used for creating the map in the appendix (p 3). We did the data processing with Python (version 3.8.5), using the Python packages pandas (version 1.1.2) and numpy (version 1.19.1).

Role of the funding source

The funders of the study had no role in study design, data collection, data analysis, data interpretation, or writing of the report. The Rockefeller Foundation did review the written manuscript before submission.

Results

From the date of launch (March 25, 2020) to Jan 14, 2022, DETECT enrolled 39 931 participants across the USA, with an over-representation of users in California (appendix p 3). In our main study period (from April 1, 2020, to Jan 14, 2022), 35 842 participants with 14 523 797 daily measurements in the USA were enrolled. After excluding 1132 users with less than 30 total resting heart rate measurements and 6183 users without step count data, 2 635 069 days without step counts or resting heart rate measurements, we were left with 4006 participants with 1 647 324 daily measurements in

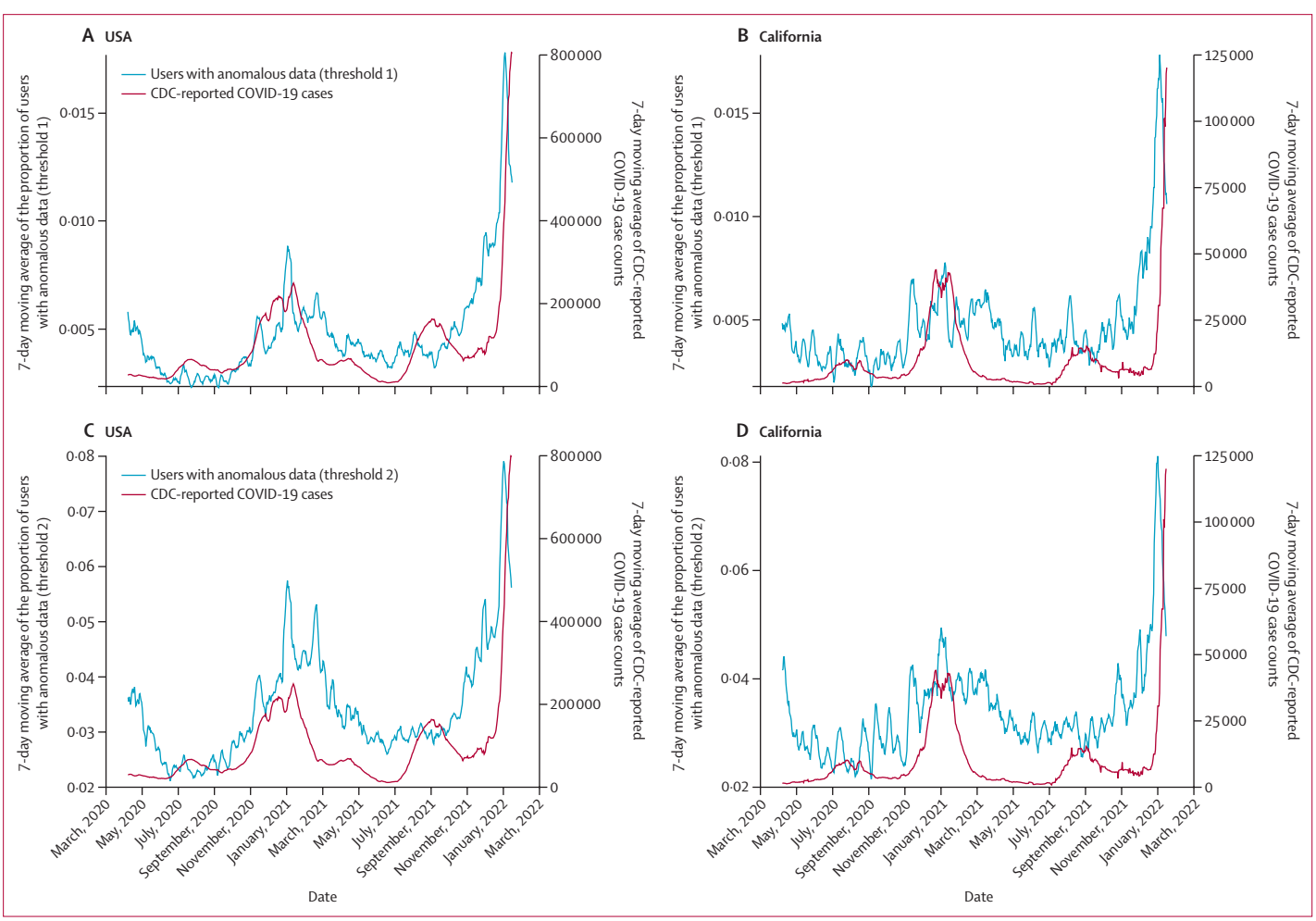

Figure 2: **DETECT users with anomalous data versus COVID-19 cases in the USA and California**

The 7-day moving average of the proportion of DETECT users with anomalous data compared with the 7-day moving average of COVID-19 case counts, as reported by the CDC, in the USA (A) and California (B), with anomalous data defined by threshold 1, and in the USA (C) and California (D), with anomalous data defined by threshold 2. Data from April 1 to April 6 were not included because the first 6 days were used to make the 7-day moving average. Naive models included just sensor data. CDC=Centers for Disease Control and Prevention. DETECT=Digital Engagement and Tracking for Early Control and Treatment.

	H_{naive} (sensor data only)	H_0 (CDC data only)	H_1 (sensor and CDC data)	p value*	Validation of H_1†
USA					
Real time	0·68 (0·64–0·72)	0·98 (0·98–0·99)	0·99 (0·99–0·99)	<0·0001	0·99 (0·98–1·00)
6 days in the future	0·79 (0·76–0·82)	0·92 (0·91–0·93)	0·97 (0·97–0·98)	<0·0001	0·95 (0·89–0·98)
12 days in the future	0·84 (0·82–0·87)	0·82 (0·79–0·84)	0·92 (0·91–0·93)	<0·0001	0·93 (0·84–0·97)
California					
Real time	0·45 (0·39–0·51)	0·97 (0·96–0·97)	0·98 (0·98–0·98)	<0·0001	0·98 (0·95–0·99)
6 days in the future	0·67 (0·63–0·71)	0·85 (0·83–0·87)	0·97 (0·96–0·97)	<0·0001	0·91 (0·81–0·96)
12 days in the future	0·83 (0·80–0·85)	0·70 (0·65–0·73)	0·93 (0·92–0·94	<0·0001	0·88 (0·75–0·95)

Data are Pearson's *r* (95% CI), unless otherwise specified. We used threshold 1 cutoffs to define anomalous days. CDC=Centers for Disease Control and Prevention. *p value for comparing the H_0 and H_1 models. †Validation was done for 26 days (Jan 21–Feb 15, 2022) and not for 32 days (Jan 15–Feb 15, 2022) as the first 6 days were used to make the 7-day moving average.

Table 2: **CDC-reported versus binomial model-predicted 7-day moving averages of COVID-19 cases in California and the USA**

California and 28 527 participants with 11 888 728 daily measurements in the entire USA (table 1). Most users had Fitbit devices rather than Apple HealthKit-connected devices (table 1).

Of the 21 933 COVID-19 swab tests reported by all participants in the development cohort, 1885 (8·6%) were positive (table 1). There were three peaks in the frequency count of COVID-19-positive swab tests throughout the study, which occurred around July 2020, November 2020–January 2021, and December 2021–January 2022 (figure 1A). Because the number of participants contributing sensor data, and probably survey data, declined with time (appendix p 4), the number of positive COVID-19 swab tests during the omicron (variant B.1.1.529) wave in the USA in December, 2021, probably reflects a larger proportion of our study population testing positive compared with earlier waves (figure 1A, B). Non-pathogen-specific symptom onset reporting (regardless of test results) was highest between April and May, 2020, and showed another peak from December, 2021, to January, 2022, during the omicron wave in the USA (figure 1C). Most participants reported receiving their first and second COVID-19 vaccines between January and June, 2021, with the uptake of boosters peaking from November to December, 2021 (figure 1D). To better understand potential differences in resting heart rate and step count by variant, we analysed changes in Z scores for these metrics in COVID-19-positive, symptomatic individuals by pandemic wave. There were similar peaks in sensor data deviation but shorter return times to baseline during the omicron wave (Dec 1, 2021–Jan 15, 2022) compared with previous waves (Jan 1, 2020–Nov 30, 2021; appendix p 5).

The 7-day moving average of the proportion of users with anomalous sensor data, as defined by threshold 1 or threshold 2, was higher during the omicron wave (approximately Dec 1, 2021–Jan 15, 2022) than during previous waves (figure 2). In fact, the sensor data did not appear to increase during the second peak of COVID-19 in the USA in September, 2021 (figure 2).

In the USA overall, there were lower Pearson correlations between the 7-day moving average of the proportion of users with anomalous data and the 7-day moving average of CDC-reported COVID-19 case counts for threshold 2 than for threshold 1, which used a higher resting heart rate Z score to identify anomalous data (figure 2; appendix p 6). Pearson correlations for the same comparison were lower for California than for the USA, although California did have a lower sample size than the USA (figure 2; appendix p 6). A lead time of 12 days in California and 12 days in the USA resulted in the highest correlations between anomalous sensor data (threshold 1) and 7-day moving averages of CDC-reported COVID-19 case counts (appendix p 6). We also found a Pearson correlation coefficient of 0·71 between the number of people with COVID-19 self-reported through the DETECT study and the number of CDC-reported COVID-19 cases in the USA in matched time, with the highest coefficient being at 8 days lead time (appendix p 6).

We used threshold 1 to define anomalous data in our negative binomial model as it showed higher Pearson correlations with the 7-day moving average of CDC-reported COVID-19 cases than did threshold 2. When the proportion of users with anomalous sensor data (x_t) was incorporated with CDC data from 3 days previously (y_{t-3}) to create the full model (H_1), the sensor variable was a significant predictor ($p<0·0001$) of 7-day moving averages of COVID-19 cases in California and the USA for real time, 6 days in the future, and 12 days in the future (table 2; appendix p 7). This result means that the sensor variable significantly improved predictions above what would be known from CDC data alone. Pearson correlations were stronger for real-time predictions compared with predictions for 6 days or 12 days in the future (table 2). When comparing H_0 with H_1 for predictions 12 days in the future, the Pearson correlation increased from 0·82 to 0·92 in the USA and from 0·70 to 0·93 in California (table 2; figure 3). Additionally, in our validation cohort of data from Jan 15 to Feb 15, 2022, which comprised 14 727 people in the USA and 2184 people in California, our H_1 model showed strong Pearson correlations for predictions 12 days in the future, with the coefficient equalling 0·88 in California and 0·93 in the USA (table 2). However, the absolute measurements were overestimates due to the validation taking place during the decline of the omicron wave (appendix p 8). Nevertheless, withdrawals from the study appeared to occur randomly (appendix p 9).

Discussion

We found that sensor data on heart rate and step count alone (H_{naive}), or when combined with CDC-reported data

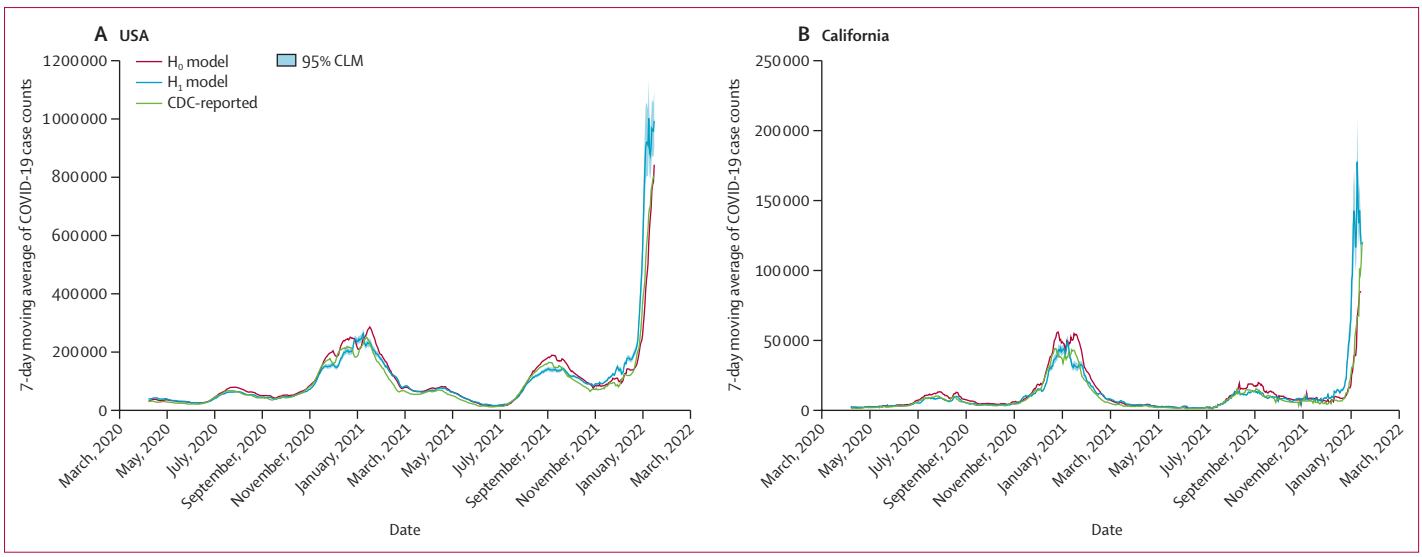

Figure 3: **Predicting 7-day moving averages of COVID-19 case counts 12 days in the future**
H_0 and H_1 models predicting 7-day moving averages of COVID-19 case counts 12 days in the future and CDC-reported 7-day moving averages of COVID-19 case counts in the USA (A) and California (B). We used threshold 1 to define anomalous days. CDC=Centers for Disease Control and Prevention. CLM=confidence limit of the mean.

on COVID-19 cases from 3 days previously (H_1), correlated with CDC-reported 7-day moving averages of COVID-19 cases in California and the USA, indicating that sensor data can provide useful information for predictions above what would be known from past case data alone. Pearson correlations for predictions 12 days in the future increased by 32·9% in California and by 12·2% in the USA from the H_0 model to the H_1 model. As expected, because CDC case reports are highly predictive for trends in the near future, Pearson correlations were stronger for real-time predictions compared with predictions for 6 days and 12 days in the future. COVID-19 self-reporting by DETECT participants also correlated with CDC-reported COVID-19 surveillance, suggesting that the reporting of test results from a moderately sized sentinel sample via a smartphone app could also provide early warning signals for the total population.

Throughout the pandemic, different SARS-CoV-2 variants, the changing demographics of people with COVID-19, and vaccination uptake might have impacted individual physiological and behavioural responses to COVID-19. The SARS-CoV-2 omicron variant is believed to result in milder symptoms[20] and physiological responses compared with earlier variants. In an examination of physiological responses among symptomatic, COVID-19-positive individuals, we found similar peaks in sensor data deviation but shorter return times to baseline during the omicron wave compared with previous waves. Because people with breakthrough infections typically present with milder symptoms, vaccination rates probably also reduced sensor data deviations among COVID-19-positive individuals. During the small peak in COVID-19 cases reported by the CDC in September, 2021, we did not find a peak in the proportion of users with anomalous sensor data. This finding could be the result of a greater proportion of breakthrough infections during this time, which are more likely to be mild or asymptomatic than infections in non-vaccinated people. This period also did not see as many symptom reports as the other waves.

The demographics of COVID-19-positive people changed throughout the pandemic, with shifts towards younger populations as older populations were vaccinated first. Resting heart rate response to vaccines has been found to vary by age;[16] therefore, resting heart rate response to SARS-CoV-2 infection probably also varies by age. Our sensor data were likely to have been influenced by mass vaccination campaigns. COVID-19 vaccination has been found to affect a user's resting heart rate, sleep, and step count data, although to a smaller extent than a SARS-CoV-2 infection does.[16,21] Influenza and other respiratory infections probably also affect the proportion of individuals with anomalous sensor data during winter months in the USA. Influenza activity was very low during the 2020–21 influenza season.[22] It was higher in the 2021–22 season, with a peak around week 52, but still lower and shorter than normal.

For **influenza activity data in the USA** see https://gis.cdc.gov/grasp/fluview/fluportaldashboard.html

Previous studies have shown that symptomatic individuals who received COVID-19 tests and tested positive had higher resting heart rate changes on average compared with those who tested negative.[15] This finding might partially explain why our higher threshold—threshold 1—performed better than threshold 2. Although the higher cutoff might have missed some people with COVID-19, it probably reduced the number of false positives caused by individuals who had sensor deviations due to other seasonal infections or non-infectious

sources. We did not use sleep data in the model as these data are frequently missing, as many devices require charging at night and users prefer not to wear them during sleep. However, as new metrics, such as respiration rate, temperature, and pulse oximetry, become more widely incorporated into fitness trackers, they are likely to further improve our ability to distinguish between infectious and non-infectious causes of sensor deviations and, potentially, between types of infection.

CDC COVID-19 surveillance data, which were used as the gold-standard comparison for this study, do not perfectly capture all cases and trends. Early in the pandemic, when testing resources were limited, people with more severe disease were prioritised for testing, meaning many individuals with milder or asymptomatic disease were probably undercounted. During the omicron wave in the USA, testing shifted to home rapid antigen tests, which were hard to obtain in many regions, resulting in inequalities.[23] Unfortunately, home testing is rarely incorporated into surveillance case counts, probably resulting in their underestimation during the omicron peak as well. In addition, moving averages also have limitations in identifying surges in case counts and case counts are subject to weekly fluctuations in reporting.[24]

The lead time we found was on a par with that of wastewater surveillance, which has a lead time of 4–10 days[25] or 2–8 days if there is no active case finding.[24] Furthermore, the correlation we found between sensor-based surveillance and CDC-reported surveillance is similar to the correlation found for wastewater surveillance and CDC-reported surveillance (Spearman r=0·7).[26] One study found that wastewater surveillance trailed symptom onset by 5 days but preceded a rise in COVID-19 cases by 4 days.[27] Because sensor data have been found to start deviating potentially before COVID-19 symptom onset,[8] sensor-based surveillance, and ideally an approach that combines all surveillance types, might provide an even earlier signal than traditional surveillance alone. Wastewater surveillance requires active and routine sample collection and testing and has low coverage across many regions of the USA.[28] With one in five people in the USA wearing a smartwatch or fitness tracker, sensor-based surveillance could provide continuous tracking, greater geographical coverage, and a lower cost solution to monitoring in areas without wastewater surveillance capabilities.

Our study has several limitations related to engagement, recruitment, and population bias. We saw a large drop off in sensor use throughout the study period, which was probably caused by known compliance issues in user wear time or syncing issues with the device app; however, withdrawals from the study appeared to occur randomly. Large-scale participation and the continued engagement of participants would allow the identification of granular geographical trends and a longer model validation time. Due to our recruitment strategy for this study, we also had an over-representation of users in California, which could have impacted the external validity of our study across the state and the country. Ethnicity data were not collected for this study. Additionally, the demographic that uses smartwatches tends to be wealthier and female, live in urban zip codes, and have a higher education, which might mean they have higher vaccination rates and a lower chance of being infected than the general population. Finding ways to make participation and sensors available to a more diverse population representing different geographical areas is key to improving the success of the DETECT surveillance platform.

Some additional limitations of our study need to be acknowledged. First, we calculated participants' mean sensor values using the entire study period rather than the period before the predicted time to improve our estimates of users' unique baselines. This approach allowed us to create predictions early in the study before we had much baseline data for users and to include participants even if they had just joined the study. Previous research has shown that daily resting heart rate has low variability, with an SD of 3 beats per min during a 2-year study period.[29] Calculating baselines from the entire study period was unlikely to change our results to a great extent, but a truly prospective study would only need to rely on information known before the prediction. It is also possible that seasonal variations in resting heart rate and step count might have impacted our results: research has shown that the mean resting heart rate is lowest in July and highest in January.[29] Second, a subset of participants who tested positive for COVID-19 might have had a prolonged elevated resting heart rate that remained elevated for several months or longer,[15] possibly resulting in the identification of anomalous days after the acute phase of their infection had ended. Third, we used the same threshold across all devices to calculate anomalous days. Device-specific algorithms for resting heart rate might also vary, resulting in the need for slightly different thresholds to identify infection; however, in this study, nearly all participants used Fitbits due to our initial recruiting efforts. Fourth, a larger sample size with a longer validation period would have provided more certainty to our findings. Finally, conveying the level of privacy and security might also present as a potential limitation. Passive data collection might require additional transparency with participants on what is being shared and with whom. In addition, where the data are stored and the protocols used to access that data might not be immediately apparent, requiring clear and concise language in the consenting process and in the app-based user experience.

To conclude, sensor-based surveillance can provide passive, continuous, and inexpensive (*vs* other collection methods) data that are orthogonal and complementary to traditional data streams. Sensor data have the potential to

provide lead times and population-level predictions of viral infection that are similar to those of other novel data sources, such as wastewater surveillance. At the same time, sensor-based surveillance has the potential to provide individuals with an early warning of an incoming infection and help to monitor their progression back to recovery. In the future, partnerships with device manufacturers, passive data collecting, and building an opt-in model at the time of purchase of these devices, as well as individual engagement through personalised feedback about their data, could improve long-term participation. The uptake of sensor-based surveillance by public health organisations and its integration with other novel and traditional viral illness surveillance strategies is crucial for creating an informative and actionable surveillance system to monitor future activity from new SARS-CoV-2 variants, the emergence of other viral illnesses with pandemic potential, and even seasonal epidemics such as influenza.

Contributors

All authors contributed to participant recruitment and enrolment. JMR conceived the study design, did the data analysis, wrote the initial draft of the manuscript, and created the figures. MG cleaned the data. GQ and MG reviewed the data analysis. All authors edited and approved the final draft of the manuscript. JMR, GQ, and MG accessed and verified the data. All authors had full access to all the data in the study, except for LMW, who works for The Rockefeller Foundation, a funder and collaborator, and had final responsibility for the decision to submit for publication.

Declaration of interests

LMW works for The Rockefeller Foundation, which funded part of this study. VK is the principal and an employee of CareEvolution. ER is the principal science officer and an employee of CareEvolution and Scripps Research. JAP is an adviser for Angiotensin Therapeutics, Precision Health, Cardiosense, and Sense AI. GQ and JMR are supported in part under a grant from The Rockefeller Foundation and the National Center for Advancing Translational Sciences, the US National Institutes of Health. All other authors declare no competing interests.

Data sharing

All interested investigators will be allowed access to the deidentified analysis dataset if they register with Scripps Research's institutional review board and pledge not to reidentify individuals or share the data with a third party. All data inquiries should be addressed to the corresponding author. The study protocol, informed consent form, and programming code are also available upon request to the corresponding author. Data will be available beginning with publication.

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