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Smartphone apps in the COVID-19 pandemic

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At the beginning of the COVID-19 pandemic, analog tools such as nasopharyngeal swabs for PCR tests were center stage and the major prevention tactics of masking and physical distancing were a throwback to the 1918 influenza pandemic. Overall, there has been scant regard for digital tools, particularly those based on smartphone apps, which is surprising given the ubiquity of smartphones across the globe. Smartphone apps, given accessibility in the time of physical distancing, were widely used for tracking, tracing and educating the public about COVID-19. Despite limitations, such as concerns around data privacy, data security, digital health illiteracy and structural inequities, there is ample evidence that apps are beneficial for understanding outbreak epidemiology, individual screening and contact tracing. While there were successes and failures in each category, outbreak epidemiology and individual screening were substantially enhanced by the reach of smartphone apps and accessory wearables. Continued use of apps within the digital infrastructure promises to provide an important tool for rigorous investigation of outcomes both in the ongoing outbreak and in future epidemics.

The 1918 influenza pandemic infected 27% of the global population and claimed 50 million lives[1]. As of February 2022, the COVID-19 pandemic had infected 6% of the global population and claimed close to 6 million lives, both of which are probably gross underestimations[2,3]. Advances in genomic sequencing, versatile vaccine platforms and manufacturing at scale have led to the development of several vaccines and their rollout at an unprecedented pace[4]. However, at the beginning of the COVID-19 pandemic we were in a disconcertingly similar situation to 1918, with no known antiviral therapy and an untested public health response to rapid tracking of new infections and timely enactment of outbreak control measures at a global scale. Pre-existing pandemic preparedness plans[5] from bodies like the World Health Organization focused on manual clinical case reporting, contact tracing and nonpharmaceutical interventions, but to this day continue to overlook the power of digital tools to rapidly scale detecting and tracing the virus and monitoring the effectiveness of interventions[6,7]. Previous studies had demonstrated the utility of digital health tools like smartphone apps for infectious disease outbreaks[8,9], yet the COVID-19 pandemic highlighted a persistent reliance on analog keystones such as in-person nasal swabs for COVID-19 testing[10], fax machines[11] for case reporting and paper vaccination cards[12].

With over 6 billion global smartphone users, apps have the potential to generate population-wide, real-time and highly informative data[13]. Private sector companies already collect geolocation, demographic, personal interest, previous purchase and other types of data for targeted marketing strategies[14]. However, to successfully realize the potential of smartphone apps in the public health domain, the challenges of digital health illiteracy[15], structural inequities[16,17] and data privacy[18,19] require investigation and mitigation. As soon as the initial case reports of COVID-19 were published from Wuhan, China[20,21] and supported by preliminary studies on the potential of multilayer data collection for public health purposes[22–24] there were widespread attempts to use smartphone apps and wearables—with varying levels of success.

Here we review and provide an assessment of the major digital app projects. The projects were selected based on coverage in both scientific and lay media and to highlight consistent constraints and challenges based on the authors' discretion. We divide the field into three major categories: (1) outbreak epidemiology, (2) individual screening and (3) contact tracing.

Outbreak epidemiology

Traditional clinical diagnosis-based viral illness surveillance in the United States is delayed by 1–3 weeks[25], giving outbreaks the chance to spread to susceptible populations before they are even identified. Smartphone app-collected data can be near real time, pull data from large numbers of people and have the potential to speed up the identification and localization of viral illness hotspots. This is important not only in regard to public health officials investigating outbreaks rapidly and increased public health prevention measures, but also for users to better understand their individual risk to make informed decisions about their day-to-day activities in an ongoing pandemic. We have divided epidemiology into (1) active user participatory surveillance, (2) passive user population-level tracking, (3) individual risk assessment and (4) viral illness forecasting.

Participatory surveillance. Phone and text message-based surveys have been used in rural regions to collect syndromic surveillance data where web-based applications may be unavailable, and have shown potential in supplementing traditional surveillance data[26]. Numerous syndromic reporting platforms, such as Flu Near You[27] in the United States, InfluenzaNet[28] in Europe, Reporta in Mexico[29] and others that allow citizen scientists to self-report influenza-like illness symptoms into a web- or app-based reporting platform have shown promise in matching the timing and magnitude of viral illness activity.

Given the overlap of symptoms between influenza and COVID-19, many of these participatory surveillance digital apps pivoted to tracking COVID-19. An app-based platform in Brazil[30] collected syndromic data from 861 participants and found that the participatory data matched spatial and temporal trends of traditional surveillance for COVID-19. This platform could be used to identify communities that should receive priority testing, and to improve surveillance in regions without health care facilities that traditionally collect surveillance data. A study among Swiss health care workers[31] found that self-reported symptoms through a web-based platform could help monitor COVID-19 and other viral

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illness activity. Similarly, the COVID Symptom Survey, launched in the United Kingdom and United States, enrolled over 4 million users and helped inform the symptomatology of COVID-19 (ref. [32]). In addition to improving surveillance timeliness, these platforms can also be used to conduct research on risk factors, vaccine effectiveness, burden of disease and more[29]. The challenge with these participatory apps is recruitment, selection bias of participant population to those with access to these platforms, individual survey fatigue with routine symptom reporting, bias towards more reporting when someone is sick rather than healthy, and a lack of specificity of symptoms to a particular viral illness.

Population-level tracking. Passive crowdsourcing of viral illness outbreak data from social media, lay media and web queries[33] can generate large-scale data that may also provide earlier warning signals than provided by traditional clinical surveillance. Healthmap's Outbreaks Near Me[34] platform automatically monitors, organizes and visualizes the location and time of infectious disease outbreaks reported globally from electronic media. This enables near-real-time visualization and identification of media-reported clusters by region, which can help public health responders identify new outbreaks more rapidly than relying on traditional surveillance data[35]. The challenge is that, by the time the media report on unusual local outbreaks, viruses may have already spread within the community.

Kinsa Health's FLUency program provided connected smart thermometers to schools to allow parents to track their child's individual risk, and schools to identify grade-level trends for viral illness outbreaks, via an app. The Kinsa thermometers had >2 million users, with publications indicating that the program improved real-time tracking of influenza-like illness[36–38] and even predicted a COVID-19 outbreak in Florida[39]. Further validation of their COVID-19 map algorithms is necessary, especially for adjudication against case rates reported by public health departments as well as clinical trials showing how they may impact outbreaks from spreading within schools. This is especially relevant as new variants emerge and with varying uptake of vaccination and nonpharmaceutical interventions among children.

Although smartphone apps have been used for outbreak tracking, the primary digital resources for COVID-19 activity were web dashboards such as the Johns Hopkins University (JHU) Covid Map[2] and Outbreak.info[40]. The JHU Covid Map provides more geographically granular data than typically provided by government public health sources, showing county-level data in the United States and province-level data in China. Outbreak.info is unique in that it provides genomic surveillance data to enable rapid tracking of the emergence of new variants throughout the globe. Many of these apps and web dashboards (Table 1) harnessed the power of big data, but also demonstrated potential sources of bias[41]. A powerful confounder was the influence of media hype and increased interest in a topic rather than specific reports or searches from sick individuals, resulting in misinformation. The impact of population-level tracking apps on morbidity and mortality reduction, public health resource allocation, prevention measures and individual risk reduction needs further evaluation.

Individual risk assessment. Several apps were intended to provide users with individual risk assessment based on population tracking in their area. The Safer-Covid[42] app gives users information about individual risk based on age, location and type of activity, to help users make informed decisions about their daily risk. Although this app is backed by the "latest available research from the National Institutes of Health (NIH), CDC and others", further transparency around the algorithm used is needed for validation. China's Health Code[43] surveillance app categorized citizens into three categories based on their risk assessment derived by mining location, payment platform and contacts data. Individuals in high-risk categories were barred from entry into certain public places, buildings and transit systems. Ideally, these individual risk assessments would also enhance use of nonpharmaceutical interventions such as mask wearing, social distancing, increased testing or stay-at-home measures. Future work needs to evaluate factors impacting their uptake, continued use and prevention of transmissions, especially in the context of potential breaches of data privacy.

Notably, none of the apps has assessed how users understand risk communication presented in the apps and how this information may impact individual or population behavior and choices. Identification of areas where individuals are participating in high-risk behavior, such as lower masking, increased mobility or low vaccination uptake, may also improve forecasting of regions most likely to experience increased viral illness activity.

Viral illness forecasting. At the beginning of the pandemic, public prevention measures relied on multiple forecasting intiatives[44] based on incident-case tracking and mathematical models, but few have truly been adjudicated with real-world data. These models had wide-ranging predictions and continued to be trained on clinical surveillance data that had their own limitations, such as changing testing strategies throughout the pandemic, variation in access to care/interventions across regions and changing syndromic definitions as the pandemic evolved. These challenges need further investigation to help inform public health pandemic strategy, rather than hinder it. Other interesting approaches to outbreak forecasting include surveillance at the pathogen level (Table 1). However, given the huge variations in predictions arising from different models over the course of the pandemic, real-time tracking may prove a complementary, or even superior, strategy for informing public health strategy.

Recommendations. The ideal outbreak tracking app would collate data from multidimensional data sources to provide users with (1) individual feedback on their probability of current infection or infection risk, (2) real-time infection rates in their local communities, work or school settings and (3) future predicted risk in their community based on forecasting models. This information needs to be useful to participants to maintain participation and engagement, with individualized action items or access to resources such as home testing, while also aggregating the data to inform early and localized public health action.

Individual screening with symptom checkers

Once an initial definition of the COVID-19 disease syndrome had been established[20,21], multiple individual screening and symptom-checker apps were developed. In the early days of the pandemic, apps for symptom checking played a crucial role because not all infected individuals were tested for objective confirmation, due to either lack of access or scarcity of testing resources such as nasal swabs and testing reagents[45]. Notably, the US Centers for Disease Control and Prevention COVID-like illness case definition also evolved as the pandemic progressed, requiring updates and education. Individual screening apps could have readily been updated to keep up with new knowledge on the infection and might have even helped inform case definition updates by including symptoms that were not commonly reported initially or became more prevalent with new variants. In the text below we divide screening symptom-checker apps into (1) active or (2) passive based on the need for user engagement, including some notable hybrid approaches as well (Table 2).

Active screening. Active-screening apps require the participant to actively interact with the tool on a frequent basis. Their primary limitation is the self-reported nature of the data, requiring the individual to actively participate in the study and report symptoms on

Table 1 | Digital epidemiology and tracking apps for COVID-19

App	Country(ies)	Developer(s)	No. of users	Outcomes published	Data sources
Active participatory surveillance					
COVID Symptom Survey	United States and United Kingdom	ZOE	>4 million	Yes	Crowdsourcing
Cantonal Hospital of St. Gallen and the Eastern Switzerland Children's Hospital	Switzerland	Hospital	1,004	Yes	Crowdsourcing
Aarogya Setu	India	Government of India	>20 million downloads	No	Crowdsourcing
Passive population-level tracking					
FLUency/Healthweather	United States	Kinsa	>2.5 million	No	Kinsa smart thermometer and JHU COVID-19 Data Repository
Outbreaks Near Me	United States and Canada	Boston Children's Hospital, HealthMap, Flu Lab and Ending Pandemics	>6.4 million	No	Crowdsourcing
Individual risk assessment					
SAFER COVID	United States	CareEvolution	N/A	No	Crowdsourcing
Health Code	China	Alipay and We Chat	900 million	No	Mining personal data related to location, payment platforms and contacts
Web-based dashboards					
JHU Covid Map	Global	JHU	N/A	Yes, detected incident cases of COVID-19 before most countries	Web searches, social media mining and adjudication with local departments of public health
Outbreak.info	Global	Open source academic collaboration	N/A	No	Epidemiologic data, genomic data and published research
Global.health	Global	Open source academic collaboration	62 million	No	Epidemiological case data
Pathogen maps					
Next Strain	Global	Open source	N/A	Feasibility, yes; outcomes, no	Multiple research groups
Spillover	Global	UC Davis, Global Virome Project	N/A	No	Global Virome Project

N/A, not available.

a daily basis. For these apps, reliance on continuous user reporting consistently ran into the challenges of smaller-than-expected sample sizes due to survey fatigue, waning user retention and participant bias, limiting the ability to make meaningful conclusions about local viral illness trends.

The first successful app of this kind was the ZOE Covid Symptom Tracker[46], which crowdsourced daily symptom information from active and sick participants in the United States and United Kingdom. Regardless of the aforementioned limitations, in the Covid Symptom Study the ZOE app was downloaded by 2.6 million users in 28 days and cemented the high positive predictive value of anosmia (loss of smell) and ageusia (loss of taste) in the symptomatology of COVID-19 (ref. [47]). The performance of the developed algorithm in the identification of COVID-19 cases showed a sensitivity and specificity of 0.65 (0.62–0.67) and 0.78 (0.76–0.80), respectively; the area under the receiver operating area curve (ROC-AUC) was 0.76 (0.74–0.78). Further prospective evaluation is needed to determine the accuracy of predicted infections versus true positives, especially as the prevalence of concurrent seasonal respiratory viruses changes. Another early active symptom-checker app was the Apple COVID-19 (ref. [48]) web app that helped people determine whether they needed a test. Although the app was widely used, there are no publications reporting the data collected to date.

Passive screening. To overcome the subjectivity of symptom surveys and the burden introduced by active screening, passive and objective biosensor data from wearables were used to detect COVID-19 and other viral illnesses. Passive screening by wearables requires minimal involvement of the individual, and initial studies demonstrated their potential to understand ambulatory physiology and identify subclinical forms of disease[49]. With an established set of symptoms for screening, wearable sensor manufacturers focused on expanding their indications to detect COVID-19.

The Digital Engagement & Tracking for Early Control & Treatment (DETECT)[50] study app used a hybrid active and passive approach by incorporating Fitbit or any wrist sensor (smartwatch or fitness band) connected to Apple HealthKit or Google Fit data, in addition to symptom questionnaires. Over 72 days this app enrolled

Table 2 | Individual screening apps with active and passive symptom checkers

App	Country(ies)	Developer	No. of users	Outcomes published	Data sources
Apple COVID-19	United States	Apple	N/A	No	Web dashboard
COVID Symptom Tracker	United Kingdom and United States	ZOE	4.7 million	Symptoms can be used to predict COVID-19	Zoe app
DETECT	United States and Australia	CareEvolution	39,000 in United States, 3,000 in Australia	Sensor data can be used to detect COVID-19 (with or without symptoms)	Fitbit, Apple watch, Google Fit
Stanford Wearables Study	United States	Device-agnostic	5,200 (latest preprint, 3,246)	Sensor data can be used to detect COVID-19 (also in presymptomatic individuals)	Any consumer wearable
Fitbit	United States	Fitbit	187,000	Sensor data can be used to predict hospitalization	Fitbit
Whoop	United States	Whoop	99,000	Respiratory rate changed in COVID-19$^+$ individuals	Whoop
Evidation	United States	Device-agnostic	7,000	Sensor data changes are different between COVID-19 and other viral illnesses	Any consumer wearable
Coronadatanspende	Germany	Robert Koch Institute	500,000	Validation of DETECT algorithm on blog	Survey plus any wearable

>35,000 users and was the first to demonstrate that passive sensor data improved prediction of COVID-19 in symptomatic cases when added to subjective symptom data[23]. The algorithm based on self-reported symptoms alone showed an AUC of 0.71 (0.63–0.69) in the detection of COVID-19 cases and, when combined with individual wearable data, the performance increased substantially to an AUC of 0.80 (0.73–0.86; Fig. 1). The proposed algorithm now integrates a broader range of signals and provides an explainable framework to highlight the most important features triggering detection[51]. Analysis of resting heart rate (RHR) for symptomatic COVID-19-positive individuals in the DETECT cohort showed an average initial increase in RHR, followed by transient bradycardia and prolonged relative tachycardia that was sustained and resolved 3 months after symptom onset[52].

In follow-up studies, novel variations in biometrics have been identified for people who have received COVID-19 vaccinations[53]. In the DETECT cohort, individual RHR baseline increased in the days after vaccination with a peak on day 2 and return to normal on day 6. In individuals who received the Moderna Spikevax (mRNA-1273, elasomeran) vaccine, in particular those who had previously tested positive for COVID-19 and individuals aged <40 years, a stronger effect was noted after the second vaccination dose than after the first (average change 1.6 versus 0.5 beats per minute). These studies exploiting continuous passive data from personal sensors could potentially be used to identify inflammatory reactions and other prognostic measures, which might shed light on variation in vaccine-induced immune responses.

Other notable projects like the Stanford Wearables Study[54] concomitantly developed a similar approach, supporting the use of wearables to detect COVID-19 even in presymptomatic individuals[55–57]. Another example is the Corona-Datenspende app, which was used by >500,000 Germans. This app had impressive engagement due to its passive nature and led to the development of a fever map to identify regions in Germany with a higher than normal number of fever cases[58]. The Corona-Datenspende cohort also demonstrated prolonged changes in vital signs for COVID-19-positive individuals, replicating and validating the results published on post-acute SARS-CoV-2 infection by the DETECT study[51,53].

More sophisticated sensors can now monitor respiratory rate and heart rate variability to improve detection accuracy, and some even have the ability to help distinguish between COVID-19 and other viral illness[59,60]. Another creative approach is to coopt wearables already in use for other applications to gather data on COVID-19: for example, the Ava bracelet—a wearable device previously adopted as a fertility tracker—was used to monitor vital signs during SARS-CoV-2 infection[61].

Recommendations. Taking all of the above considerations into account, the ideal sensor-based screening app should integrate several aspects currently presented in multiple apps. First, to be accessible to an under-represented and underserved population, it should be able to integrate the information from any sensor, including that from less sophisticated mobile devices with limited features. Similarly, the app should adapt not only to the desired level of participation of the individual, allowing the participant to easily self-report information on contact with positive individuals, test results or vaccine status, but also be able to function in the absence of this information. The data from the app should be interpretable, highlighting the most important features used in the detection[51]. Most importantly, it should enable the detection of COVID-19 in real time based on past data[57]. Furthermore, the ideal app should be regularly updated to identify not only COVID-19 cases, but also other infectious and noninfectious factors impacting one's health, becoming a passive screening companion for the individual that can trigger questions or ask for feedback from the individual only when necessary.

Wearable technology continues to evolve, with smartphone camera apps now measuring facial plethysmography to detect vital signs[62] and face masks using synthetic biology to allow SARS-CoV-2 virus detection, enabling real-time testing and reporting through associated apps[63]. The next generation of digital apps for symptom tracking will continue to add another layer of objective granular biofluid chemistry data, such as sweat, saliva and gut microbiome, to supplement wearable sensor vital signs and subjective questionnaires[9]. From a care delivery standpoint, further investigation is needed to determine whether variation in biometric changes actually leads to testing and adjudication with a positive COVID-19 test in an individual and their known social contacts.

Contact tracing

As COVID-19 testing capabilities enabled the identification of greater numbers of SARS-CoV-2-positive cases, most national COVID-19 apps transitioned from case tracking to contact tracing.

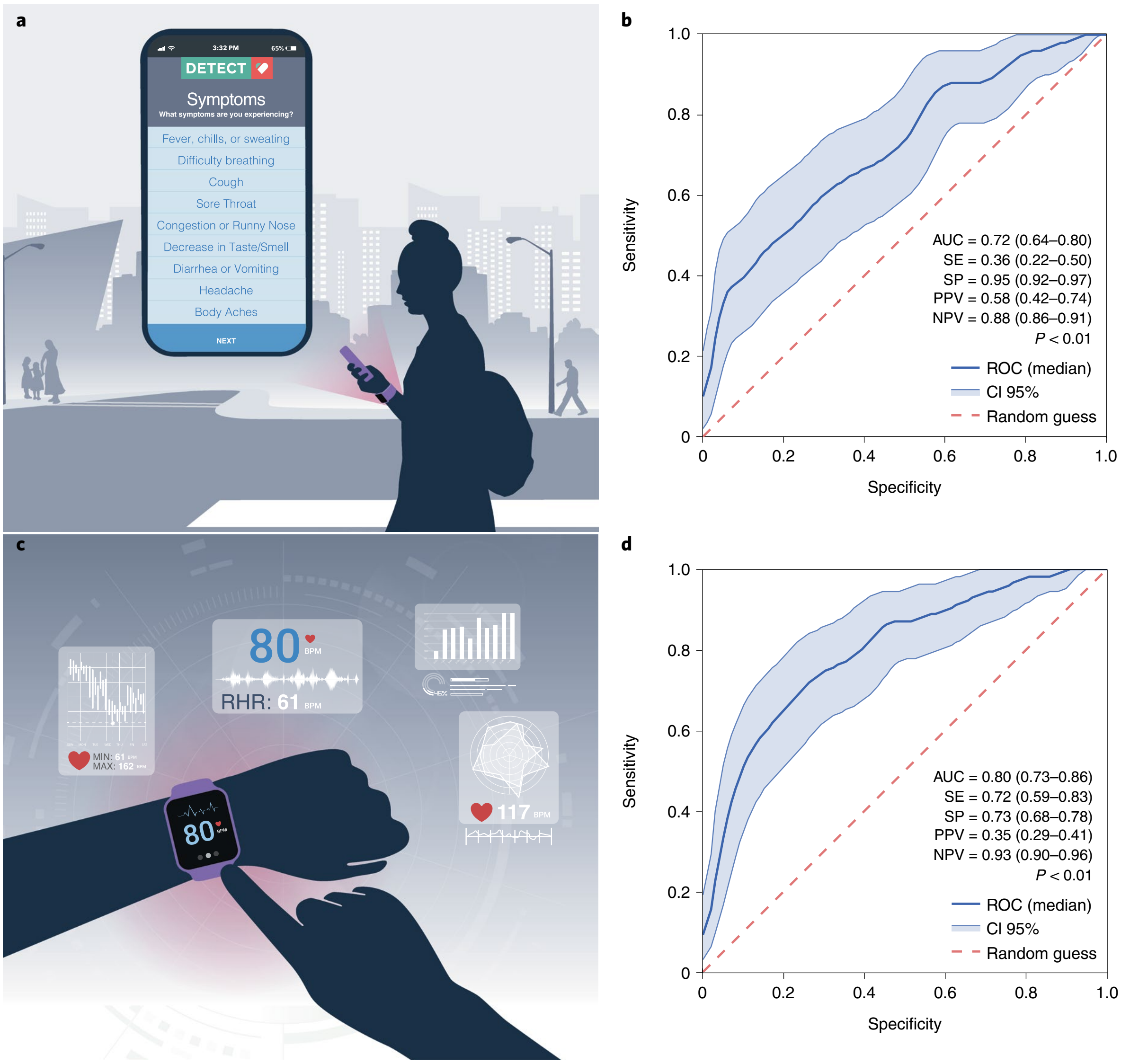

Fig. 1 | DETECT study results[23]. **a**–**d**, The DETECT study evaluated the added utility of wearable data to symptom questionnaires. **a**, Screenshot of symptom questionnaire on the DETECT study platform. **b**, The algorithm based on self-reported symptoms alone had a ROC-AUC value of 0.72. **c**,**d**, Passive wearable data from any wrist sensor connected to the Apple HealthKit or Google Fit (**c**) was then added to the subjective symptom questionnaire, and demonstrated a ROC-AUC value of 0.80 (**d**). CI, confidence interval; SE, sensitivity; SP, specificity; PPV, positive predictive value; NPV, negative predictive value.

Contact tracing was the most ubiquitously used COVID-19-related smartphone app function, despite the dearth of real-world outcomes. The standard of care for local departments of public health was to manually conduct systematic interviews of infected individuals and then notify their exposed contacts[64]. With the rapid spread of COVID-19 and the relatively limited manpower available at public health offices, contact tracing apps provided a scalable alternative. An Oxford University study had already demonstrated that contact tracing could be an effective outbreak mitigation strategy, but only on mathematical models[24]. Smartphone apps were a natural choice because smartphones can interact with each other, thereby detecting proximity between individuals using technologies like Bluetooth Low Energy systems and others. Additionally, global position systems, proximity to cell towers, Internet protocol addresses and international mobile equipment identity numbers could help geolocate movements of specific individuals[65].

Contact tracing, however, comes at a substantial cost to data privacy and security. Private sector companies aggregate and use these data for marketing purposes, but the pros and cons of preserving data privacy by tapping into this network during a pandemic continue to be debated. During the pandemic adoption and public acceptance and implementation of contact-tracing apps depended on local geopolitics, existing technology infrastructure and cultural differences. China[66], South Korea[66,67] and Taiwan[68], due to geographic proximity to the incident cases of COVID-19, initially overlooked privacy concerns and retrospectively mined data from private sector organizations such as mobile payment platforms, social media, public transit records and closed-circuit television footage for outbreak tracking and tracing. Realizing the potential of collecting these data in real time through smartphone apps, many contact-tracing and exposure-notification apps were developed but ran into the rate-limiting step of requiring downloading and activation to be functional[69].

In April 2020, Google and Apple joined forces to develop the Google Apple Exposure Notification (GAEN) system[70] that allowed health agencies to provide exposure notifications without the requirement of an app download. The GAEN system was intended for public health use but did raise major privacy concerns,

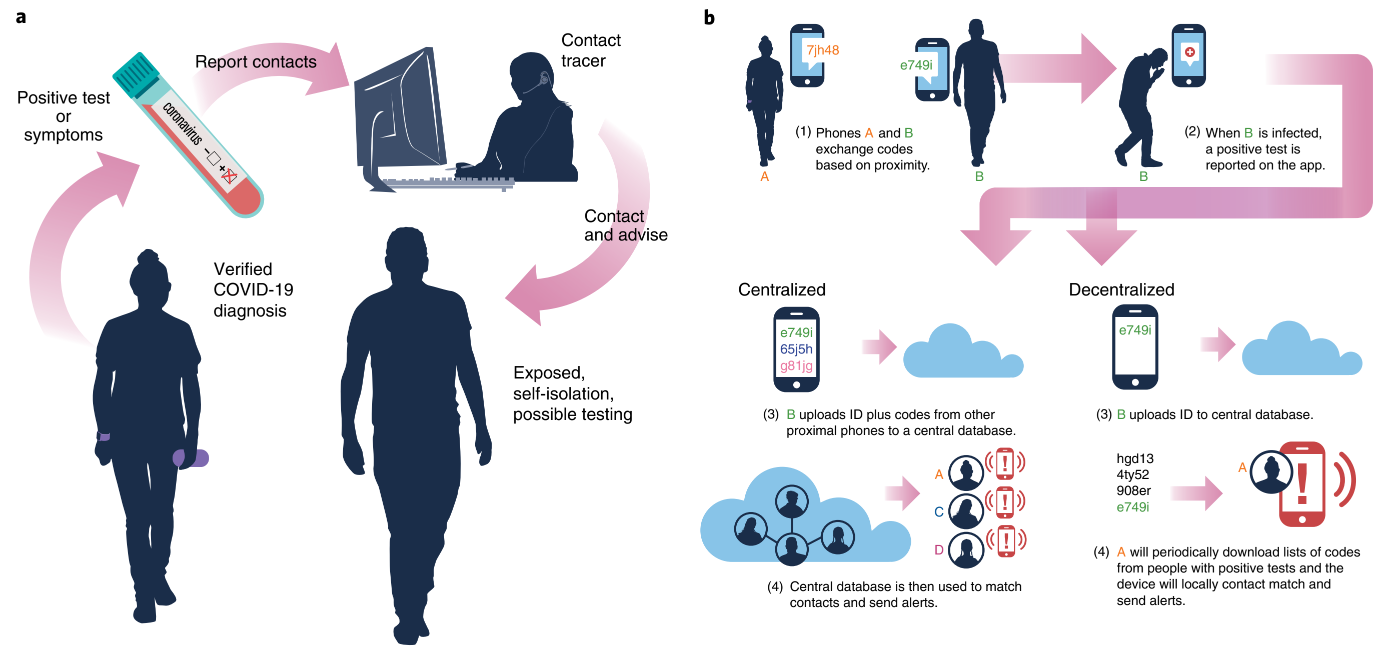

Fig. 2 | Manual and digital contact tracing. a, In manual contact tracing, a positive test would induce the cascade of reporting to a local department of public health, which would then lead to contacting the infected individual to identify exposed social contacts and inform them. **b**, In digital contact tracing, when two phones are in close proximity they exchange codes. For centralized contact tracing, when an individual is infected their phone communicates infection information to a central server that identifies all other phones that have been in proximity, to notify exposures. In decentralized contact tracing, the smartphone regularly downloads codes of an infected individual's smartphones and then compares them to contact history locally and informs the user if there is a match.

leading to the development of privacy-preserving frameworks that contact-tracing apps could opt to follow. Most contact-tracing apps can be divided into (1) centralized, where matching and notification are done at a central server or (2) decentralized, where matching and notification are done by the individual smartphone (Fig. 2). We discuss these in turn below.

Centralized approaches. China's Health Code app had >900 million users in >200 cities[43] while India's Aarogya Setu app had 50 million users within 13 days[71], demonstrating the reach and speed of smartphone apps in large populations when promoted by a central authority. Other examples of centralized contact tracing apps are Singapore's TraceTogether[72] and Australia's COVIDSafe[73], which were downloaded by 17 and 25% of the nations' populations, respectively. Although there was significant outreach for all these centralized approaches, none met their targets and all had substantial challenges, including app download issues, hoax apps, incompatibility with other apps, lack of access to smartphones in vulnerable populations and, most critically, data privacy and security concerns and fears of invasive government surveillance[74,75]. Amnesty International even called out Bahrain's BeAware, Kuwait's Shlonik and Norway's first Smittestop contact-tracing apps as "endangering the privacy and security of their populations"[76]. In Saudi Arabia, the Tawakkalna contact-tracing app became required for school entry for any child >12 years[77]. Notably, despite the higher national penetrance levels with centralized apps, there are still no outcomes publications as to whether these approaches were successful in mitigating waves of the pandemic. Although most unitary states and some democracies still use a centralized approach, most nations have pivoted to decentralized approaches.

Decentralized approaches. An example of the pivot from centralized to decentralized—and the most well-studied contact-tracing app—is the United Kingdom's National Health Service (NHS) COVID-19 app. From its launch on 24 September 2020 to the end of December 2020, the app was downloaded onto 21 million phones and sent out 1.7 million notifications in England and Wales (Fig. 3). In a rare-outcomes evaluation publication on digital contact tracing, every 1% increase in the number of NHS COVID-19 app downloads led to a 0.8–2.3% reduction in the number of COVID-19 infections[78]. Additionally, approximately one case was averted for each user consenting to notification of their contacts; in absolute numbers, Wymant et al.[78] suggest that 100,000–900,000 cases were averted by the NHS COVID-19 app over the 13-week study. The main limitations of the Wymant et al.[78] study are confounding factors that are encountered in any observational study, notably sociodemographic factors such as urbanization and socioeconomic status among others. However, the report clearly demonstrates that digital contact-tracing apps can be a powerful supplement to non-pharmaceutical interventions during a pandemic.

Despite the availability of many other contact-tracing national-, state- and organization-level apps, the only other app with published outcomes is the SwissCovid app. In a city-level (Zurich, Switzerland) retrospective analysis, 537 app users received a positive SARS-CoV-2 test result, 324 of whom had received and entered an upload authorization code[79]. This code triggered an app notification for 1,374 proximity contacts and led to 722 information hotline calls, with an estimated 170 calls receiving a quarantine recommendation. In this case, although there is a positive signal for contact-tracing apps leading to quarantine recommendations and even identification of SARS-CoV-2, it represented only up to 5% of those captured by manual contact tracing, suggesting that contact tracing should not replace, but instead supplement, manual contact tracing to push nonpharmaceutical interventions.

In the United States, due to the lack of a national contact tracing app, most states released their own versions of decentralized contact-tracing apps. A recent investigation on the uptake of US digital contact tracing[80] showed that, as of May 2021, a total of

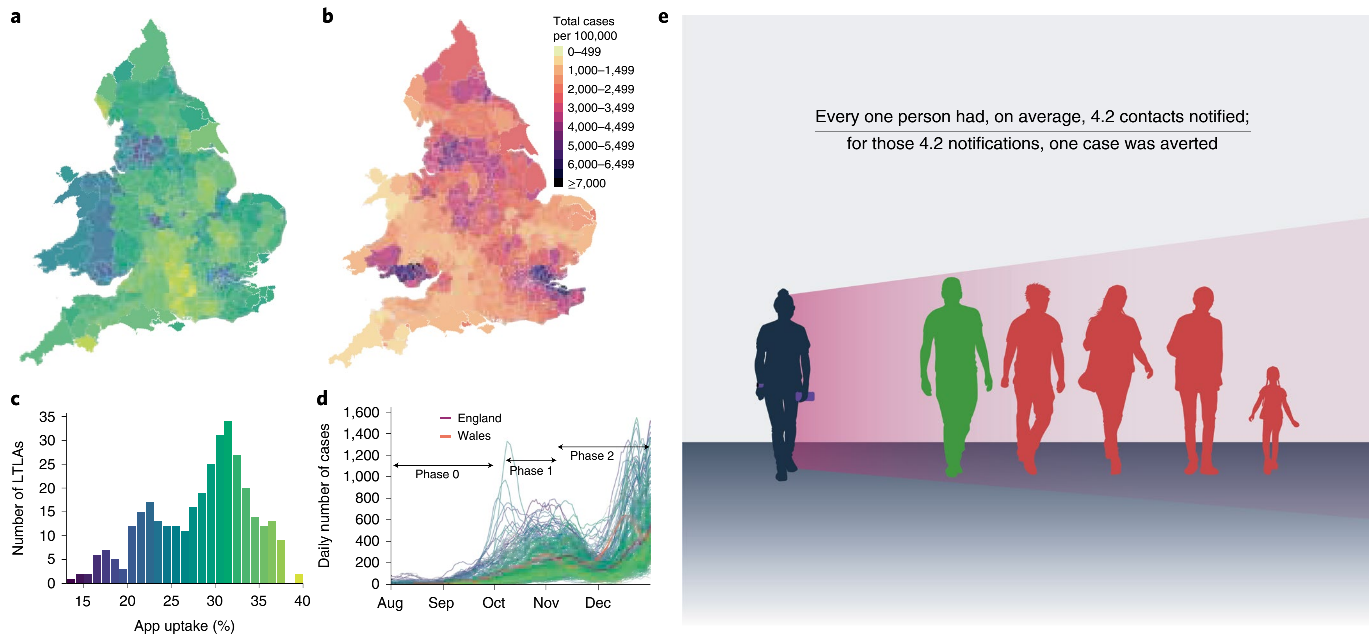

Fig. 3 | Geographic variability of NHS COVID-19 app uptake and cases of COVID-19. a–e, Geographical distribution of COVID-19 cases in England and Wales[78]. Map (**a**) and histogram (**c**) of NHS COVID-19 app uptake by local-tier local authorities (LTLAs). Colors in **a** indicate app uptake as shown in **c**. **b**, Cumulative cases of COVID-19 per 100,000 population over analysis phases 0 (before app launch), 1 (1 October 2020 to early November 2020, with first version of app) and 2 (early November to 31 December 2020, with improved version of app). **d**, Seven-day rolling mean of daily cases of COVID-19 per 100,000 population. **e**, Ultimately the NHS COVID-19 app showed that for every one person who consented to notification of contacts, on average 4.2 contacts were notified and one case of COVID-19 was averted.

36.7 million Americans had opted into exposure-notification apps. Furthermore, although there have been no rigorous outcomes publications looking at the effectiveness of contact-tracing apps in the United States, media coverage has reported them as not worth the risk to privacy[81].

Initial studies had suggested a target adoption rate of 60% for contact-tracing apps for pandemic mitigation; however, none of the US states hit this target[82]. Notably, although the NHS COVID-19 app also did not meet the generally accepted adoption target of 60%, it was still considered remarkably successful at 29%, suggesting that further investigation of target adoption rates is needed. In this respect, some studies have reported alternative indices for measurement[83] to test association with hard outcomes while others have looked at data-driven testing programs informed by close-contact notification[84]. However, there is a dire need to better understand the utility of digital contact tracing in public health, and to ascertain and optimize the adoption rate necessary to justify the potential risks to privacy.

Although prepandemic laws like the Health insurance Portability and Accountability Act, the European Union's General Data Protection Regulation and other local regulations such as the California Consumer Privacy Act provided some guidance, no overarching federal or global regulations specifically mention contact-tracing apps[85,86]. Data privacy concerns prompted the development of privacy-preserving frameworks like the Decentralized Privacy-Preserving Proximity Tracing and Pan-European Privacy-Preserving Proximity Tracing that contact-tracing apps could opt to follow; at this present time, however, there is no accountability. Despite these initial steps, data privacy concerns continue to be the primary reason for low participation rates and the most common reason that countries have hit the pause button on contact-tracing app rollouts. Exacerbating the ethical debate was the use of apps and wearables for quarantine compliance. Examples include mobile geofencing in Taiwan, trackable wristbands in India and South Korea, trackable tokens in Singapore and even ankle shackles in Australia, none of which have outcomes reported in the literature available to justify such measures[87]. Overall, peer-reviewed studies are needed to evaluate the effectiveness of digital contact-tracing apps in other regions to justify the extent to which the technology was used during COVID-19.

Recommendations. The ideal contact-tracing app would work in real time, preserve data privacy, comply with local regulations, lead to actionable and measurable outcomes, be on local devices to avoid bandwidth issues and, for public health purposes, not require opting in. In addition, although contact tracing has largely been based on contact proximity, it should also take into account local biometric, pathogen and environmental data to improve and potentially rank the type of exposure and avoid issues like the 'pingdemic'[88]. Although this may seem like a moonshot, with federated learning approaches enabled by edge computing and the evolution of decentralized blockchain technology, the solution might be closer than we think.

Discussion and outlook

Despite the widespread use of smartphone apps as public health tools during the COVID-19 pandemic, and with vast amounts of data aggregated, very few reports have been published detailing outcomes that can inform pandemic strategy. Outbreak-tracking apps that harness big data from multiple sources can provide real-time data about viral illness trends that can be updated frequently, but may be subject to confounders including greater media coverage and participation bias. Individual-risk apps are available but have no data on case reduction or increased use of nonpharmaceutical interventions. Symptom-checker apps and wearables show promise with advances in sensor functionality for infection screening, but a need still exists for truly passive and unobtrusive individual screening systems that become a part of daily life and can

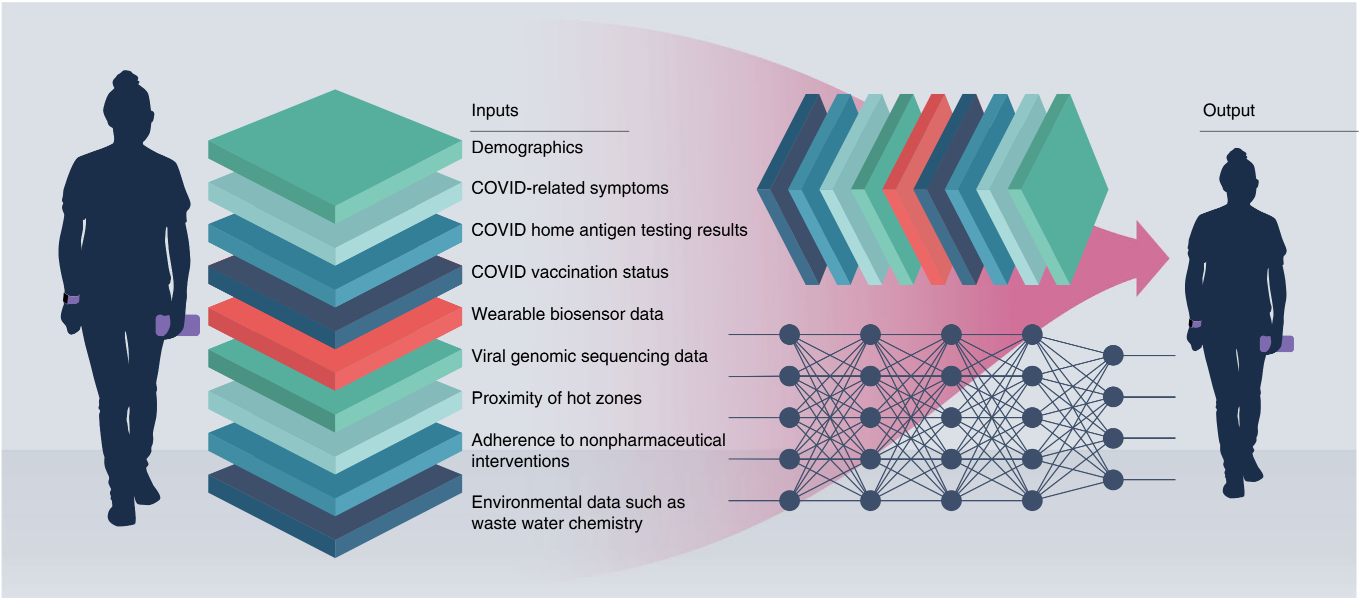

Fig. 4 | A possible future multiple integrated app? In the current pandemic, while many apps were made to address specific public health challenges, it is now time to merge datasets and analyze multiple layers of data such as demographics, symptoms, testing, vaccination status, wearable sensor, genomic sequencing, geolocation, personal behavioral risk and environmental data to better inform pandemic strategy, individual risk and risk communication, to ultimately push adherence of impactful actions such as nonpharmaceutical interventions and vaccinations.

function as a supplementary public health tool during a pandemic. Contact-tracing apps are abundant, but only a few have associated peer-reviewed publications reporting outcome data that demonstrate the success of contact tracing and exposure notification; in this context, is there enough evidence to justify the risks to data privacy and security of such apps? Furthermore, to begin a rigorous evaluation of the efficacy of contact-tracing apps we need first to ensure the representativeness of the data and data standards. Although contact-tracing apps are abundant, use was less frequent in Africa and South America, highlighting the challenge of global inequity—especially as many low-to-middle-income countries still do not have the ability to fully vaccinate their populations. Given the ubiquity of these apps, further investigation is necessary around barriers to adoption, optimal privacy preservation within different geopolitical environments, effective implementation (engagement and retention) with cultural inclusivity, and overall effectiveness (considering varying technology infrastructures).

As we transition to the current state of the pandemic, with countries debating reopening and reclosing public spaces, it would be ideal to rapidly identify new COVID-19 hotspots and vaccination epidemiology to continue our fight against the SARS-CoV-2 and its variants. COVID-19 testing has expanded from a limited number of real-time PCR and antibody tests at local departments of public health to being democratized and made freely available at retail pharmacies and pop-up tents/stores, and even for home use[89]. Many of these home tests have accessory apps to display and share results. With varying vaccine/booster acceptance rates in different areas of the world, apps can be used to battle vaccine hesitancy[90] as we continue to push vaccine and booster uptake. Myths around vaccinations and their side effects can be rebutted using data and evidence from apps that monitor the physiologic effects of vaccines and infection in a cohort over time[53]. Furthermore, in the age of smartphone apps it is a travesty that paper vaccination cards, which can easily be falsified, were selected as the most common proof of vaccination. Digital vaccination apps should be promoted and can be used for vaccination tracking to finally solve the true percentage of vaccinated individuals required for herd immunity.

Data privacy and participant bias are consistent challenges of any global digital public health intervention. Although privacy-preserving frameworks exist, universal adoption with a top-down approach will always be a challenge. It might be time for developers of smartphone and wearable apps to build privacy preservation and deidentification options at the edge (that is, user level). Ethical frameworks and committees should be developed to oversee the use of these technologies at a global scale[91]. Accessibility, despite the global penetration of smartphones, will also never be 100%, especially in lower-income, rural and low-technical-literacy populations. Furthermore, retention within health apps continues to be a challenge and can potentially skew data, with certain populations under-represented in biomedical research more likely to drop out without culturally customized initiatives for engagement. Another evolving challenge in the current phase of the pandemic is notification fatigue, which is the result of too many poorly working apps that are unnecessarily alerting the individual or notifying them to self-isolate, sometimes even creating a pressure not to get tested despite having symptoms. This pingdemic effect demonstrates that even digital tools that work effectively have limitations when it comes to behavioral health. An outbreak-tracking app may mark every neighborhood as a hotspot, a symptom-tracking app may ask you to take a test every day or multiple times a day and a contact-tracing app may ask you to isolate all the time. Outcomes evaluations could inform how risk and outbreak communication can be tailored to have maximal impact.

This Review's primary limitation is also its conclusion—that there is a glaring need for more published reports detailing outcomes-related investigations analyzing the efficacy of COVID-19 apps. Although we have attempted to provide a global review of major digital app projects, the final selection of projects was limited to what has been highlighted by both scientific and lay media coverage and the authors' discretion.

In infectious disease, digital health tools and apps now open new opportunities for both individuals and public health systems. For asymptomatic individuals, apps make it possible to know when vital signs have changed from baseline, raising awareness of the potential for being infected; for public health authorities, the development of a cluster of individuals from app data can enable early detection of a possible outbreak. They also have relevance in the context of pharmacologic intervention; with the FDA clearance of subcutaneous monoclonal antibodies for the prevention of COVID-19 for individuals with known exposure and oral therapies for symptomatic individuals with COVID-19, app data could better guide the use of relevant treatment regimens. The combination of wearable sensor data notification and rapid home antigen testing results also promises to provide greater confidence in infection diagnosis, thereby facilitating the more efficient initiation of contact tracing.

Looking forward, the integration of the functionality of several different apps into a single, user-friendly one would be a substantial practical advantage. Through digital tracking of continuous vital signs via wearable sensors, along with relevant clinical data, there now exists the potential for remote monitoring of patients with COVID-19, obviating hospital admission. This would require assessment and validation through large, prospective clinical trials that compare remote monitoring with standard care, to prove non-inferiority and safety of digital surveillance. At the population level, an obvious and attainable future direction is to build public health systems with multidimensional inputs that include mobility data, comprehensive and fully encrypted electronic health data, wearable or environmental/atmospheric sensors for infectious agent wastewater surveillance, genomic sequencing data and real-time analytics (Fig. 4). These layers of orthogonal data would provide an enhanced view for any individual with a smartphone and web access as to their specific risk level, along with a better path to prediction of new outbreaks. These represent exciting directions and challenges to develop, but there is little sign that they are being pursued and, despite the data being available, there is inadequate reporting of outcomes from apps in peer-reviewed publications. It is time to respect and optimize the power of these digital health tools.

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Additional information

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