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Selectivity of digital trace data: The case of the UK COVID-19 contact tracing apps

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Non-technical summary

People running surveys are increasingly considering using smartphone apps as part of their data collection processes. Because surveys aim to find out things about the broader population, it is important to know who is included and excluded in any given data collection process. For potential collection of data via smartphones, that means understanding who would be able to or would choose to use the smartphone app.

We use the case of the COVID-19 contact tracing apps in the UK to investigate how people who used the apps differ from people who do not. For the COVID-19 apps, the differences based on the characteristics we looked at were generally not very large. Some of the largest differences we found were related to age, with the youngest age category (45 and lower) being overrepresented in the group who told us they had downloaded the app by about 10 percentage points and the oldest group (76+) being underrepresented by about 8 percentage points. We also find that people who never use the internet are underrepresented in the group of app downloaders by about 9 percentage points.

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Abstract:

Digital trace data — including from smartphone apps — are increasingly considered for research use, either as adjuncts to survey data or on their own. Understanding selection of smartphone app usage is therefore important in considering the potential of the data they generate for research purposes. We use data from the Understanding Society COVID study, which asked about uptake of the UK COVID contact tracing apps, to investigate (1) selection rates across stages of using the app, including smartphone ownership, smartphone compatibility with the app, app installation, and app use, (2) associated selection biases, and (3) reasons for not installing the app. To examine selection rates, we report population estimates of the percentages who reach various stages. Bias is analyzed by examining differences between characteristics of the overall sample and the sub-samples at the different stages of app use. We report population estimates of reasons for not installing the app. We find multiple contributions to substantial overall losses to selection, with only 36% consistently using the app. Biases by socio-demographic and health groups are generally moderate, with the largest biases in app downloads being around 10-11 percentage points for certain categories of age, education, and a measure of digital use. The most common reported reasons for not using the app are that they were taking precautions (33%) or privacy/trust concerns (24%). While derived from survey data about COVID tracing apps, these findings provide broader insights into likely issues of selection and bias when considering smartphone digital trace data for research.

Keywords:

Smartphone, survey, Understanding Society, bias, selection, digital trace data, digital epidemiology

JEL classification:

C80, C83, C88

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Abstract

Digital trace data — including from smartphone apps — are increasingly considered for research use, either as adjuncts to survey data or on their own. Understanding selection of smartphone app usage is therefore important in considering the potential of the data they generate for research purposes. We use data from the *Understanding Society* COVID study, which asked about uptake of the UK COVID contact tracing apps, to investigate (1) selection rates across stages of using the app, including smartphone ownership, smartphone compatibility with the app, app installation, and app use, (2) associated selection biases, and (3) reasons for not installing the app. To examine selection rates, we report population estimates of the percentages who reach various stages. Bias is analyzed by examining differences between characteristics of the overall sample and the sub-samples at the different stages of app use. We report population estimates of reasons for not installing the app. We find multiple contributions to substantial overall losses to selection, with only 36% consistently using the app. Biases by socio-demographic and health groups are generally moderate, with the largest biases in app downloads being around 10-11 percentage points for certain categories of age, education, and a measure of digital use. The most common reported reasons for not using the app are that they were taking precautions (33%) or privacy/trust concerns (24%). While derived from survey data about COVID tracing apps, these findings provide broader insights into likely issues of selection and bias when considering smartphone digital trace data for research.

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1. Introduction

Rising costs and declining response rates have raised questions about the long-term viability of survey data collection. At the same time, the need for more timely data at finer granularity for research to inform policy has never been greater.

Over the past few decades, researchers have been seeking alternatives to traditional surveys, especially those using interviewers. In the early part of the 21st century, this took the form of non-probability volunteer panels of Internet users (also called opt-in panels or access panels; see, e.g., Baker et al. 2010; Callegaro et al. 2014). This period also saw the formation of large-scale volunteer databases (LSVDs; see Brayne and Moffitt 2022), such as the UK Biobank or *All of Us* in the U.S., that have Internet-based data collection as a core part of their methods. The same period has seen the rise of "big data" as an alternative or complement to surveys (for reviews, see Japec et al. 2015; Hill et al. 2020). Researchers have often contrasted "organic data" with "designed data" (Groves 2011) or "found data" with "made data" (Taylor 2013; Harford 2014). This is reflected in developments in digital epidemiology, which refers to the use of big data from social media, search engines, mobile apps, and wearables for health research (Fallatah and Adekola, 2024).

The term "big data" implies a monolith of methods or sources; however, there are many different types of big data (as there are many types of surveys), and they vary in their quality or error properties (as do surveys). The rubric "big data" often includes administrative data sources. However, in this research we consider data that are sometimes called "digital trace data" (Bach et al. 2021; Hinds and Joinson 2018), and we use this term here. The sources of digital trace data include both passive methods carried out directly by researchers (e.g., web-scraping, GPS or phone log data obtained from service providers) and more active methods that require some form of opt-in or consent from the data subject (e.g., social media posts) or actions such as downloading an app or installing a web tracker or sensor to collect data (Revilla, Ochoa and Loewe 2017; Keusch et al. 2019, 2020, 2022; Wenz, Jäckle and Couper 2019).

The COVID-19 pandemic and subsequent global lockdown accelerated this movement toward alternative data sources, in part because of the suspension of many survey data collections, particularly those using face-to-face interviewing, and the unprecedented demand for timely data to inform actions to combat the pandemic. As Kohler (2020, p. 93) noted, "The COVID-19 crisis created an enormous demand for rapid research results." The rapid rise in adoption of these alternative data sources has raised questions about the issues of representation and quality (see, e.g., Blom et al. 2021; Klingwort and Schnell 2020).

Following the rise in alternative data sources has come a growing body of research exploring the quality of these data. A number of authors have extended the total survey error framework to include various types of big data (see, e.g., Amaya, Biemer and Kinyon 2020; Hsieh and Murphy 2017; Sen et al. 2021). A particular concern is with selection biases, where participation is restricted to those with access to digital technologies (coverage error) or those who choose to participate in activities that generate digital trace data (akin to nonresponse error).

Our paper follows this long tradition, from work using face-to-face surveys to explore the selection biases associated with landline (e.g., Groves and Kahn 1979) and cellular (e.g., Blumberg, Luke and Cynamon 2006) telephone ownership and access, to more recent work examining the same for Internet access and smartphone use (Couper et al. 2018). Researchers are also exploring the stated willingness to use research apps for a variety of purposes (e.g., Keusch et al. 2019; Revilla, Couper and Ochoa 2019; Struminskaya et al. 2020; Wenz, Jäckle and Couper 2019), and the actual use of such apps (e.g., Jäckle et al. 2019, 2022; Keusch et al. 2019; Kreuter et al. 2020; Struminskaya et al. 2021).

Against the backdrop of the changing landscape of data for social science research and public policy, along with the increased demand for more – and more frequent – data accelerated by the COVID-19 pandemic, this paper focuses on one type of potential error (selection bias) in one type of digital trace data or digital epidemiology, that is, data that was not generated for the primary purpose of epidemiological research.

This is a case study on the use of COVID-19 tracking apps in the United Kingdom, which has relevance beyond this particular application, to other types of digital trace data.
In a provocative paper, Klingwort and Schnell (2020) argue that "COVID-19 Apps Are Useless [for research]." They go on to note that "the use of smart devices suffers from under-coverage and nonresponse, which are rarely addressed by proponents of digital epidemiology" (p. 99). Our case study illustrates the sample loss at each stage of selection into the use of a contact-tracing app and examines the selection biases introduced at each stage of the process, focusing on both socio-demographic characteristics and substantive variables of interest. In the next section we review the relevant literature on contact-tracing apps in the context of the COVID-19 pandemic.

2. Background

Contact tracing is an essential activity in all stages of a pandemic, preventing spread within the population in the early stages, helping to curtail transmission when a disease is widespread, and blocking and containing new outbreaks during the 'tail' of the infection (Rizzo 2020; Baraniuk 2020). Given how quickly the COVID-19 virus spread, traditional contact tracing methods were insufficient. Many countries promoted the use of contact-tracing apps to take advantage of the widespread use of smartphones and technology features (e.g., Bluetooth proximity detectors) to facilitate tracing, on the assumption that mobile phone proximity detection may serve as a good approximation for close contact (Maccari and Cagno 2021, p. 11).

If successful, digital contact tracing solutions have the potential to address limitations of traditional contact tracing, such as scalability, notification delays, recall errors and contact identification in public spaces (Kleinman and Merkel 2020). However, the success of app-based contact tracing depends in large part on people's willingness to use the app (Altmann et al. 2020). Close examination of factors related to the uptake and effectiveness of digital contact tracing apps is needed, not only in relation to the COVID-19 pandemic but also their potential for future outbreaks of other infectious diseases (Colizza et al. 2021).

A number of simulations have examined the required adoption levels of contact-tracing apps to minimize the spread of the virus. Based on a simulation in the United Kingdom, Hinch et al. (2020) found that the epidemic could be suppressed with 80% of all smartphone users using the app, or 56% of the population overall. Currie et al. (2020) tested various models based on early adoption of the COVIDSafe app in Australia. At an app uptake of 27% of smartphone users (the estimated level at the time), the app could reduce the projected total number of new cases by one-quarter if other conditions were met. If uptake reached the possible maximum of 61% (representing their best estimate of the proportion of the population that had a smartphone at the time, was in the 14+ age range likely to use the app, and had sufficient technical literacy to download it), the reduction could be more than half.

These simulations suggest a substantial majority of the population with smartphones must download and use the app for it to be maximally effective in reducing transmission. These simulations focus on the proportion of the total population using the app, not on specific subgroups. For instance, if those most vulnerable to contracting COVID-19 (the elderly, those with comorbidities, Black and minority ethnic groups) are downloading the app, but those more likely to spread the virus (those who are not following social distancing guidelines, those who feel they are at low risk from the virus, etc.) are not, the effectiveness of the app may be diminished.

Understanding socio-demographic differences and behavior around the use of apps for contact tracing is critical to maximize their use and potential benefit. Similarly, understanding reasons for using (or not using) the app would help guide targeted public health campaigns to increase app use. To this end, several studies have examined people's stated willingness to download and use a COVID-19 contact-tracing app. Given the urgency of the task, many of these used nonprobability online surveys of opt-in or access panel members, a group that is already Internet-savvy and more likely to have smartphones and be early adopters of technology (see Baker et al. 2010; Callegaro et al. 2014).

Altmann et al. (2020) conducted a large anonymous online survey in several countries to measure public support for the digital contact tracing of COVID-19 infections under different installation policies (opt-in or voluntary installation versus opt-out or automatic installation by the government). Under the voluntary (opt-in) condition, about 75% of respondents said they would probably or definitely download the contact-tracing app if available. They examined a number of demographic covariates of willingness. While support was high across demographic groups, groups more likely to install the app included the youngest age group (18-34 vs. over 71), those who always carry their phone with them (versus rarely), and those with one or more comorbidities. The probability of installing the app was also positively associated with trust in the government. They also asked about respondents' reasons for or against installing the app. Concerns about government surveillance (mentioned by 42%) and cybersecurity (vulnerability to hacking; mentioned by 35%), and concerns that usage of the app may increase feelings of anxiety (26%) were most frequently mentioned by those opposed to using the app. The most frequent reasons in favor of the app were willingness to protect family and friends (68%), a sense of responsibility toward the community (53%), and a hope that the app may stop the epidemic (55%).

Bachtiger et al. (2020) conducted an online survey among a sample of registered National Health Service (NHS) users of the Care Information Exchange (CIE) in the UK. Among respondents, 60% reported being willing to participate in app-based contact tracing. Of those who said 'no', 67% cited privacy reasons. Difficulty understanding government rules and reporting an unconfirmed belief of having previously had and recovered from COVID-19 were associated with a decreased inclination to download the app.

O’Callaghan et al. (2021) conducted an open access web survey in the Republic of Ireland, with adult participants invited to respond via e-mail and messaging apps and posted on a university website and on popular social media platforms, prior to launch of the national app solution in July of that year. Slightly more than half (54%) of respondents said they would definitely download a contact-tracing app, while an additional 30% said they would probably do so. They found that the oldest and youngest groups were most likely to install the app. COVID-related worry was associated with willingness to install—those who said they were “not at all worried” about COVID-19 were far less likely to say they were willing to install the app. The most common reasons in favor of downloading the app were the potential to help family and friends and a sense of responsibility to the wider community. Reasons against downloading the app included fear that technology companies or the government might use the app technology for greater surveillance after the pandemic.

A non-probability online survey by Velicia-Martin et al. (2021) found indications that expectations of an app being useful increased with additional education, and that intention to adopt an app was highest amongst people over 35. Conversely, a non-probability online survey in Singapore by Saw et al. (2021), found COVID app uptake to be associated with having made behavioral modifications in response to the pandemic (e.g., use of hand sanitizers, avoidance of public transport, and preferring outdoor venues), but did not find significant associations with demographic characteristics. Qualitative interviewing of participants in German-speaking countries found trust in authorities, privacy and voluntariness amongst the concerns raised in relation to digital contact tracing apps (Zimmermann et al. 2021).

Of the studies that have investigated COVID app uptake, few have examined questions of device compatibility and respondents' ability to install apps. In one exception, Blom et al. (2021) conducted a survey in Germany on a probability-based online panel. They estimated that 81% of the population had both a compatible device and the ability to install apps onto it, and that 35% were willing to install and use it, reporting higher access (92%) but lower willingness (31%) amongst potential spreaders, and lower access among vulnerable groups (62%).

Jonker et al. (2020) conducted a discrete choice experiment in a non-probability online panel designed to be representative of the Dutch population on potential uptake of a COVID-19 app. Predicted app adoption rates ranged from 59% to 66%, with a rate of 64% for the most realistic scenario. Adoption rates strongly varied by age group (46% for those age ≥75 years versus 79% for those 15-34 years). Educational attainment, the presence of serious underlying health conditions, and the respondents' views on COVID-19 infection risks were also correlated with the predicted adoption rates. The findings on demographic correlates are supported by earlier papers on the adoption and use of general health and wellbeing apps (e.g., Robbins et al. 2017; Bol, Helberger and Weert 2018; Cho and Kim 2020; Rising et al. 2020).

To date, we are aware of only three studies that have looked at reported rates of download and use following public release of a COVID-related app. Thomas et al. (2020) conducted a national quota survey among online panel participants in May 2020 to investigate the uptake of the Australian Government's COVIDSafe app and examine the reasons why some Australians had not downloaded it. Of those surveyed, 37% reported having downloaded the app, 19% intended to do so, while 28% refused to do so, and 16% were undecided. Reported reasons for not downloading the app included privacy (25% of those who refused or were undecided), technical concerns, including phone being too old or not having enough storage space (24%), the belief that social distancing was sufficient and the app was unnecessary (17%), and distrust in the government (11%). They found that app downloads increased with age (those 65+ having the highest proportion of downloads). They also found that knowledge about the COVIDSafe app varied among participants, with some being confused about its purpose and capabilities.

Von Wyl et al. (2021) conducted a survey in October 2020 among members of an online access panel in Switzerland. Overall, 47% of participants reported using the SwissCovid app (up from 44% in a study wave conducted in July 2020). Higher income, more frequent internet use, better adherence to mask-wearing recommendations, and being a non-smoker were associated with an increased likelihood for app uptake. Higher levels of trust in government and health authorities were also associated with a higher app uptake probability. The most frequent reasons given for app non-use was lack of perceived benefit of the app (37%), with 23% not having a compatible phone and 22% citing privacy concerns.

A study of uptake of the German digital contact tracing app — drawn from two different non-probability access panels — found higher reported uptake rates among respondents with an increased risk of severe illness, but lower rates among those with a heightened risk of exposure to COVID-19 (Munzert et al. 2021).

This review points to significant gaps in our knowledge about uptake levels of a COVID contact-tracing app. The existing literature sometimes addresses incidence of downloading the app, but tells us little about the continuous use of the app as directed. The review also points to gaps in knowledge regarding differences in uptake, not only between key socio-demographic subgroups, but also those with different risks of contracting the virus and different behaviors in terms of potentially spreading the virus. Understanding these differences and the reasons behind non-uptake will help understand the selection biases in the use of apps for public health specifically, and for research purposes more broadly.

3. Research Questions

With this background in mind, our paper sets out to use a large national survey (*Understanding Society*) to examine the selectivity of users of the UK contact tracing apps and explore reasons for non-use. We have three broad research questions:

RQ1: What are the selection rates at the different stages of using contact tracing apps?

Sample loss is likely at each stage of selection, decreasing sample sizes for analysis and potentially increasing selection biases (see RQ2). Conditional on completing the survey, what percentage of the sample report having a smartphone, having a smartphone that is compatible with the app, installing the app, and having the tracing active? Note that we do not examine selection that may occur prior to completing the survey (i.e., attrition in *Understanding Society*, non-response to the survey).

RQ2: Which selection biases are introduced at the different stages?

Here we are interested in which types of people are excluded because they do not have a compatible device. Which types are excluded because they choose not to use the app although they have a compatible device? Even if sample loss (see RQ1) is minimized, if this loss is differential across different types of people, any inferences made on the basis of the remaining participants may be biased.

RQ3: What are reasons respondents who had a smartphone gave for not installing the app?

To minimize sample loss and selection bias in studies such as this, it is important to understand the barriers to participation.

4. Data

The survey and analysis sample

This paper is based on respondents who gave a full interview in English to the November 2020 web or telephone COVID-19 *Understanding Society* surveys. *Understanding Society*: The UK Household Longitudinal Study, is a representative sample of households in the UK (University of Essex, Institute for Social and Economic Research 2024). The study is based on a clustered and stratified probability sample that over-samples key ethnic minority groups. Starting in 2009, all members of sample households aged 16 and over have been eligible for annual interviews. In April 2020, all adults in households that had participated in at least one of the previous two annual interviews were invited to a COVID-19 survey (n=42,330; University of Essex, Institute for Social and Economic Research 2021). This excluded sample members who were adamant refusals or mentally or physically unable to make an informed decision to take part, and those with unknown postal addresses or addresses abroad. The COVID-19 study was fielded as a monthly web survey from April to July 2020, and then every two months. In May and November 2020, a subset of non-respondents to the web survey who live in households where no-one uses the internet regularly were invited to a telephone survey instead.

A total of 19,997 sample members were invited to the November survey, with the web survey period running from 24 November to 1 December 2020 and the telephone survey taking place from 23 November to 5 December 2020. In total, 12,168 respondents completed the full survey, for an overall response rate of 61%. The analyses are based on those respondents who completed the full survey in English (n = 12,160). After excluding those respondents with missing or inapplicable data for any of the variables used in the analyses, we are left with an analysis sample of 11,801 cases. See Appendix A1 for the documentation of the analysis sample selection.

Data on age, ethnicity, education and household income were derived from previous waves of the annual interviews. The outcomes and other covariates are from the November web and telephone COVID-19 surveys (University of Essex and Institute for Social and Economic Research 2021).

Outcome measures

The COVID-19 test and trace app was compatible with Android smartphones running OS version 6.0 or higher and iOS smartphones running OS 13.5 or higher. There were different versions of the app across countries in the UK: in England and Wales the "NHS COVID-19" app, in Scotland the "NHS Scotland Protect Scotland" app, and in Northern Ireland the "HSC StopCOVID NI" app. Functionally, however, these apps were comparable.

To examine the different stages of selection into the digital trace data from the COVID-19 app, we use a sequence of outcome measures. Full details on the survey questions underpinning these variables and how they were coded are provided in Appendix A2.

- Whether the respondent has a smartphone (yes, no).

- Whether the smartphone operating system is compatible with the app (yes if Android or iOS, no otherwise).
- Whether the operating system version is compatible with the app (yes, no).
- Whether the respondent has downloaded the app (yes, no).
- Whether they turned on the tracing function in the app (yes always or when they leave home, no).

Reasons for not downloading the app were measured by asking Android and iPhone smartphone users who reported not downloading the app *"Why haven't you downloaded the <app>?"* and showing a list of 11 response options from which respondents could choose all that applied to them. Those who reported "other reasons" were asked to specify. These open-ended responses were coded and combined with the answers from the closed question.

Covariates

To examine biases that occur at different stages of selection into the digital trace data generated by the COVID-19 app, we use a range of covariates related to socio-demographic characteristics, health, and digital behaviors. See Appendix A2 for details on how the variables for household income, clinical risk and digital use were derived.

- Sex (male, female).
- Age group (≤45, 46-65, 66-75, 76+).
- Ethnicity / race (white; Black, Asian, Mixed, or other non-White).
- Highest educational qualification (degree, secondary school qualification, other qualification, or none).
- Monthly household net income (quintiles).
- Self-reported health (poor or fair, good, very good, excellent).

- Clinical risk of catching COVID-19 (extremely vulnerable, vulnerable, not vulnerable).
- Whether living with any children aged under 16 (yes, no).
- Whether living with any older adults aged over 70 (yes, no).
- Mean digital use score (every day, several times a week, several times a month, once a month, less than once a month, never, missing).

5. Methods

All analyses are weighted to account for differential inclusion probabilities and non-response. Analyses are conducted accounting for the complex sampling design, with clustering and stratification.

We examine the losses at the different stages of selection into the use of the app (RQ1), by tabulating the estimated proportions of the population who have a smartphone, who have a compatible operating system, etc., through to the proportion who use the tracing function of the app.

We examine selection biases (RQ2) at three key stages: whether people have a smartphone, whether they have a compatible operating system, and whether they have installed the app. We follow the approach by Couper et al (2018) and use the covariates listed above to estimate the proportions in each category in the full sample. We then estimate the proportions in each category for each of the subsets (smartphone users, compatible OS, app download). For each respondent characteristic and subset, we compute a bias statistic that equals the difference in an estimate y between the selected subset (p) and the full sample (f):

$$bias(y) = y_p - y_f$$

We calculate the standard error of the estimated bias following Lee (2006) as:

$$se(y_p - y_f) = \frac{n_f - n_p}{n_f}\sqrt{var(y_p) + var(y_{np})}$$

Where y_{np} is the estimate for the subset that is excluded. We then test the significance of the bias estimates using large sample z-tests, dividing each estimated bias by its standard error.

To examine the reasons why people with a compatible smartphone do not install the app (RQ3) we tabulate the reasons reported.

6. Results

RQ1: What are the selection rates at the different stages of using contact tracing apps?

Table 1 shows the selection rates at each stage of using the tracing app. While 83% of respondents reported having a smartphone, fewer (74%) had one that was compatible with the app. Fewer than half (44%) of all respondents reported having downloaded the app (59% of those with a compatible smartphone). While a large majority (83%) of those who downloaded the app reported turning the tracing on (always or always when leaving the home), this only represented about a third of all respondents to the November survey (36%). Cumulatively, these stages result in substantial sample loss.

Table 1: Selection rates at different stages

		Weighted percentages		
	N	**Overall**	**...of those with compatible OS version**	**...of those who reported downloading app**
Full analysis sample	11801	100.0	-	-
Has a smartphone	10278	82.8	-	-
Has an Android or iPhone smartphone	10141	81.1	-	-
Has an Android or iPhone smartphone with compatible OS version	9139	73.7	100.0	-
Downloaded the app	5633	43.5	59.1	100.0
Turns the tracing on - always/always when leaves home	4678	36.0	48.8	82.6

RQ2: Which selection biases are introduced at the different stages?

Next, we look at the extent to which the sample loss is differential across a selection of socio-demographic, health and digital use related variables. Table 2 shows that in the full sample, 54.6% are female. Among those with a smartphone 53.9% are female, meaning a bias of -0.7 percentage points. While small, the difference between the two estimates passes the conventional threshold for statistical significance (p=0.011). Comparing those who have a smartphone with compatible operating system to the full sample, the bias increases slightly to -1.0 (p=0.009). Comparing those who downloaded and installed the app to the full sample, the bias decreases to 0.1 and becomes non-significant (p=0.851). As with all binary variables, the biases for men mirror those for women and are therefore not included in the table: 45.4% of the full sample are men; among those with a smartphone men are over-represented by 0.7 percentage points, etc. Biases are small for sex (male/female) and ethnicity/race (white/black, Asian, mixed, other non-white), ranging from 0.1 to 1.2 in absolute values for all sub-groups in these categories. However, given the size of the sample, most of the biases observed each reach the conventional threshold for statistical significance.

For many characteristics, the biases at the different stages of selection into app use compound (that is, increase over successive stages). This is reflected in the mean absolute bias computed across all characteristics, which increases from 3.0, to 3.9 to 4.1 across the three stages. For example, people with a degree are over-represented among smartphone users by 4.5 percentage points, among those with a compatible OS version by 5.6 percentage points, and among those who installed the app by 9.5 percentage points. There are exceptions. Those not living with children under the age of 16 are under-represented among smartphone users (by -4.2 percentage points), among those with compatible OS versions (by -5.8 percentage points), and those who installed the app (by -4.8 percentage points). That is, the bias compounds at the first two stages, but at the last stage it seems that those not living with children are in fact more likely to install the app than those who are living with children. Another exception is clinical risk. Those who are not clinically vulnerable are over-represented by 6.8, 8.7, and 7.0 percentage points at the different stages; those with moderate clinical risk are under-represented by -6.2, -8.0, and -6.2 percentage points. That is, those at moderate risk are under-represented among smartphone users, and more so among those with compatible OS versions. But they are more likely to install the app than those with no clinical risk, reducing the extent to which they are under-represented, and the no risk group are over-represented among those who installed the app.

Focusing on the last stage, those who installed the app, there are clear patterns. The oldest age group (76+) are under-represented by -8.2 percentage points, while the youngest age group (≤45) are over-represented by 9.5 percentage points. Those without qualifications are underrepresented by -7.0 percentage points, while those with a degree are over-represented by 9.5 percentage points. Those in the lowest income quintile are under-represented by -8.3 percentage points, while those in the 4th and 5th quintiles are over-represented by 4.5 and 5.6 percentage points. Those with poor/fair health are under-represented by -5.3 percentage points, while those with very good or excellent health are over-represented by 4.0 and 1.5 percentage points. Those who are not at clinical risk are over-represented by 7.0 percentage points, those at moderate risk are under-represented by -6.2 percentage points; however, those at high risk are only marginally under-represented by -0.8 percentage points. Those not living with children under 16 are under-represented by -4.8 percentage points and those who are living with older people are under-represented by -3.9 percentage points. Finally, those with a mean digital use score of “several times a week” are over-represented by 10.9

percentage points, while those with a score of "never" are under-represented by -9.4 percentage points.

Table 2: Selection biases introduced at different stages of using the contact tracing apps

		Full sample		Has smartphone		Has compatible OS / OS version		Reported app download	
		N	**Percent**	**Bias**	***p*-value**	**Bias**	***p*-value**	**Bias**	***p*-value**
Sex	Female [omitted: Male]	6885	54.6	-0.7	0.011	-1.0	0.009	0.1	0.851
Age group	76+	1079	11.5	-7.1	<0.001	-8.3	<0.001	-8.2	<0.001
	66 to 75	2501	15.0	-2.5	<0.001	-4.1	<0.001	-3.1	<0.001
	46 to 65	5095	35.4	2.7	<0.001	2.3	<0.001	1.9	0.004
	45 and lower	3126	38.1	6.8	<0.001	10.0	<0.001	9.5	<0.001
Race / ethnicity	White [omitted: Black, Asian, Mixed, other non-white]	10698	92.2	-0.9	<0.001	-1.2	<0.001	1.1	0.048
Education	No qualification	607	9.5	-4.9	<0.001	-6.1	<0.001	-7.0	<0.001
	Other qualification	844	8.3	-1.8	<0.001	-2.4	<0.001	-2.9	<0.001
	Secondary school qualification	4432	42.6	2.2	<0.001	2.9	<0.001	0.3	0.683
	Degree	5918	39.7	4.5	<0.001	5.6	<0.001	9.5	<0.001
Monthly household income	≤ £1648	1857	19.9	-5.4	<0.001	-6.6	<0.001	-8.3	<0.001
	> £1648 and ≤ £2556	2248	20.2	-1.5	<0.001	-2.1	<0.001	-3.8	<0.001
	> £2556 and ≤ £3566	2551	20.1	1.5	<0.001	1.9	<0.001	2.0	0.002
	> £3566 and ≤ £4846	2568	19.9	2.4	<0.001	2.8	<0.001	4.5	<0.001
	> £4846	2577	19.9	2.9	<0.001	4.0	<0.001	5.6	<0.001
Self-reported health	Poor or fair	1821	19.2	-3.4	<0.001	-4.6	<0.001	-5.3	<0.001
	Good	3784	32.3	-0.1	0.871	0.0	0.911	-0.2	0.838
	Very good	4931	38.1	2.3	<0.001	3.3	<0.001	4.0	<0.001
	Excellent	1265	10.4	1.2	<0.001	1.3	<0.001	1.5	<0.001
Clinical risk	Not clinically vulnerable	6512	55.8	6.8	<0.001	8.7	<0.001	7.0	<0.001
	Moderate risk (clinically vulnerable)	4512	38.2	-6.2	<0.001	-8.0	<0.001	-6.2	<0.001
	High risk (clinically extremely vulnerable)	777	6.0	-0.6	0.006	-0.6	0.012	-0.8	0.021

Children	Not living with any children (<16 years) [omitted: Living with children]	9202	75.9	-4.2	<0.001	-5.8	<0.001	-4.8	<0.001
Older adults	Living with at least one older adult (70+ years) [omitted: Not living with older adults]	1918	13.2	-3.0	<0.001	-3.9	<0.001	-3.9	<0.001
Mean digital use score	1 (Every day)	270	3.0	0.6	<0.001	1.0	<0.001	1.2	<0.001
	2 (Several times a week)	3589	34.3	6.3	<0.001	9.3	<0.001	10.9	<0.001
	3 (Several times a month)	3662	26.2	3.3	<0.001	3.5	<0.001	3.7	<0.001
	4 (Once a month)	2798	18.0	-0.5	0.071	-2.2	<0.001	-3.8	<0.001
	5 (Less than once a month)	673	5.0	-1.3	0.002	-2.2	<0.001	-2.8	<0.001
	6 (Never)	489	10.3	-8.3	<0.001	-9.4	<0.001	-9.4	<0.001
	Digital use questions not answered	320	3.2	-0.1	0.445	0.0	0.912	0.1	0.679
Mean absolute bias				3.0		3.9		4.1	
Total N		11801		10278		9139		5633	

Notes: Weighted percentages. Biases = percentage point difference between the prevalence in the subset and the full sample of respondents.

RQ3: What are reasons respondents who had a smartphone gave for not installing the app?

Those who had an Android or iOS smartphone but reported not downloading and installing the app were asked their reasons for not doing so. The most common reason (reported by 32.6% of respondents) related to the view that installing the app was unnecessary as they were already taking precautions or using other methods of contact tracing. About a quarter of respondents mentioned privacy or mistrust as reasons for not doing so. A number of respondents also mentioned technical limitations, including having an incompatible smartphone (10.3%), insufficient storage space (9.8%), concern over battery life (4.9%), and so on. Only 5.2% of respondents reported being unable to find or download the app.

Table 3: Reasons for not installing the contact tracing app

	Number of mentions	**Weighted percentage of respondents**
Taking precautions including not going out, another family member having the app, or using another app/method	1435	32.6
Concerns about privacy or trust in government / company	1029	24.0
Mistrusts information or app reliability	1016	23.8
Have not got around to downloading it	781	17.3
Smartphone old, operating system not compatible	571	10.3

I don't have storage space for the app	388	9.8
Other reasons	230	5.4
Not knowing how to download or use it inc. unable to find in app store	257	5.2
I think the app will use up too much battery	195	4.9
I didn't know there was an app	140	3.4
Doesn't want to inc. views it as unnecessary	117	3.1
Not allowed at work	97	1.8
Not wanting to use Bluetooth, GPS, data allowance	27	0.7
Total responses	6,283	

Notes: Based on 4,508 respondents who had iPhone or Android smartphones but reported not downloading the app. Respondents could mention multiple reasons. See Appendix A2 for details of where some categories in this table are merged, including merging provided reasons and coded free-text reasons provided respondents who selected "other".

7. Discussion and Conclusions

This study examines selection biases in digital trace data from the COVID-19 apps that the UK population was asked to use, starting in 2020. By asking respondents in the UK Household Longitudinal Study about their ownership of compatible smartphones, whether they installed and used the app, and reasons for not installing it, we are able to examine reasons for exclusion from these digital trace data, and the associated biases in terms of socio-demographic and health characteristics.

We found substantial sample loss across the various stages of app use (RQ1). While most respondents (83%) reported having a smartphone and the majority (74%) reported having one compatible with the app, fewer than half (44%) of all respondents reported downloading the app. If we further restrict the sample to those who reported turning the tracing on (always or always when outside the home), we are left with about a third of all respondents to the survey (36%). In other words, 26% of the population could not use the app because they did not have a compatible device, a further 30% chose not to download it, and 8% did download but did not always turn the tracing on. This limited the test and trace app to just over a third of the population.

In RQ2 we explored the extent to which these sample losses resulted in selection or participation biases in selected socio-demographic, health, and digital use related variables available on the full sample. While many of the observed biases are statistically significant (given the large sample size), most are relatively small. The mean absolute bias for smartphone users is 3.0 percentage points. This increases to 3.9 when further restricting the sample to those with a compatible smartphone and to 4.1 percentage points when additionally restricting the sample to those who reported downloading the app. This suggests that, despite the substantial sample loss at each stage of the study, on average the observed biases do not show substantial increases over the stages.

As expected, younger people are over-represented across all stages. Similarly, those with higher levels of education and income are over-represented at all stages. Those who report being in poor or fair health are under-represented across the stages, as are those who are clinically vulnerable (but not those who ae extremely clinically vulnerable). While not a linear trend, those with lower levels of digital activity tend to be substantially under-represented. These results suggest that while the biases are not substantial and do not appear to increase much across the stages of selection, there are some key exceptions, including both demographic variables (age, education, income, digital use) and health-related variables. While the former could potentially be addressed with additional weighting adjustments, the latter are a particular concern for health-related apps.

In RQ3 we explored the reasons why people with a compatible device did not install the app. The most common reason reported (by 33% of respondents) relates to the view that installing the app was unnecessary as they were already taking other precautions. This may be specific to the app we studied (a COVID-19 contact tracing app), but may be relevant to other kinds of apps (e.g., activity trackers for those who already track their physical activity, or are physically inactive). Privacy and trust issues were reported by nearly a quarter of respondents (24%), as were mistrust in the information provided by the app. Technical problems, such as lack of storage space, not knowing how to install the app, not finding the app in the app store, or limited battery were only mentioned by between 5% and 10% of respondents. In fact, 17% said they simply had not got around to installing it yet.

A key limitation of this study is that it focused on a particular app at a particular fraught point in time (the COVID-19 pandemic). Nonetheless, we believe that these findings have implications for other studies asking survey respondents to download and use smartphone apps to actively or passively report data. This may be particularly true of self-selected samples, such as accelerometry or GPS tracking studies based on volunteers with the required devices and willing to download and use apps to track their behavior.

There may be several possible mechanisms for the differential coverage and subsequent biases we observed. One is a “healthy person bias,” which suggests that those who join volunteer cohorts, use activity trackers, download health-related apps, etc., are more healthy and physically active than the general population (see Couper and Jäckle 2024 for a review of this literature). A competing mechanism may be termed “risk bias”: those who download and use a COVID-19 tracking app are those who feel more vulnerable or are at greater risk (i.e., older, less healthy people. With the limited indicators at our disposal, we are unable to disentangle these two mechanisms, and this is an area for further exploration. Another possible mechanism is the “digital divide” (see, for example, Hargittai 2010): those who have access to and use digital technologies are younger, better educated, have higher income and potentially healthier than the general population. Each of these (or other) mechanisms may help to understand *who* we may lose when conducting studies such as this, and the reasons *why* we are losing substantial numbers of participants.

The general conclusion is that while substantial sample loss occurs across several stages of selection into the use of a contact-tracing app, these generally do not result in substantial biases. Nevertheless, there are several key exceptions, pointing to the need for further research across different populations and applications.

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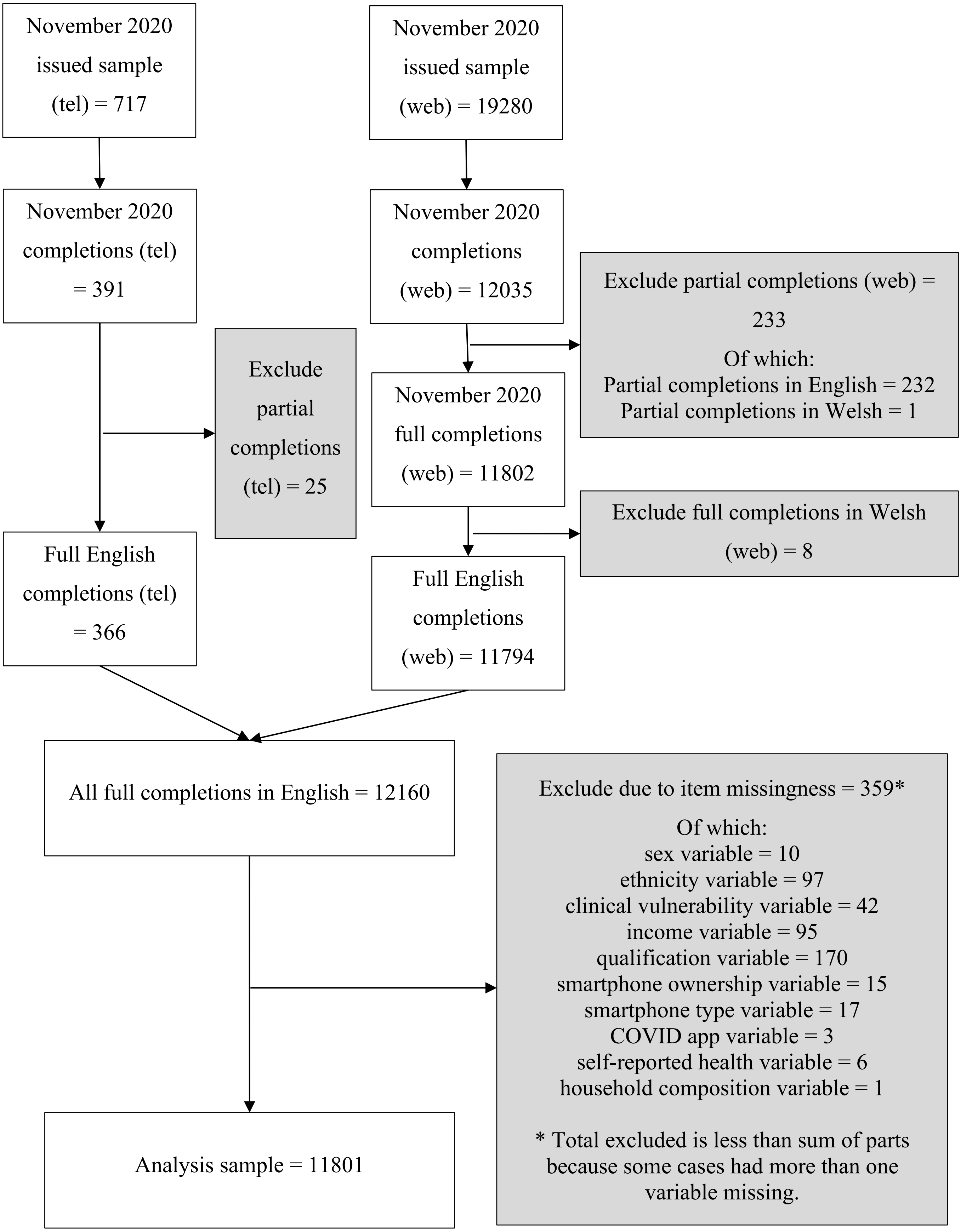
Appendices

A1. Analysis sample


November 2020 issued sample (tel) = 717
November 2020 issued sample (web) = 19280
November 2020 completions (tel) = 391
November 2020 completions (web) = 12035
Exclude partial completions (web) = 233
Of which:
Partial completions in English = 232
Partial completions in Welsh = 1
Exclude partial completions (tel) = 25
November 2020 full completions (web) = 11802
Exclude full completions in Welsh (web) = 8
Full English completions (tel) = 366
Full English completions (web) = 11794
All full completions in English = 12160
Exclude due to item missingness = 359*
Of which:
sex variable = 10
ethnicity variable = 97
clinical vulnerability variable = 42
income variable = 95
qualification variable = 170
smartphone ownership variable = 15
smartphone type variable = 17
COVID app variable = 3
self-reported health variable = 6
household composition variable = 1
* Total excluded is less than sum of parts because some cases had more than one variable missing.
Analysis sample = 11801

A2. Survey questions and variables used for analyses

Smartphone use

Respondents were asked *"Do you personally have a smartphone?" ("Yes", "No")*.

Smartphone operating system

If yes, they were asked *"What type of smartphone do you use – is it an Android, iPhone, or some other type of smartphone?" ("Android", "iPhone", "Other type")*.

Smartphone operating system version

We used a combination of self-report and passive measurement (user agent string; see Callegaro 2010) to determine smartphone compatibility. For 5633 respondents, we were able to ascertain that they had a compatible smartphone because they reported having installed the relevant COVID app. To identify whether other respondents' smartphones were compatible with the app, we asked all smartphone users *"What is the make and model of your smartphone?"*. The text field contained a lookup function that suggested smartphone makes and models as the respondent typed. The make and model was subsequently matched to data scraped from www.gsmarena.com, a database of smartphones, to retrieve the highest operating system version with which the smartphone was compatible. However not all operating systems could be identified in this way; this resulted in information for a further 3842 Android and iOS users. For the remaining respondents, we next used information from the January 2021 COVID-19 survey, where we asked all Android and iOS smartphone users to self-report the operating system version of their phone *("What is the operating system version of your smartphone? This might be just one number, or up to three numbers* *separated by full stops."*), accompanied with instructions on how to find their operating system version that varied dependent on whether the respondent reported being an Android or iPhone user and whether or not they were completing the survey on their smartphone. From this we ascertained the compatibility for a further 183 Android and iOS users. Where we were not able to ascertain compatibility from respondents' self-reported smartphone model (November) or self-reported operating system version (January), we examined the user agent string (UAS) from the device on which they completed the surveys in November and January, for those completing via the web. The UAS is a small string of identifying information that provides details of some features of a device accessing a website (in this case the survey website), including its operating system and operating system version. This allowed us to ascertain compatibility data for a further 165 respondents using November UAS data and 22 respondents using January UAS data. Where none of these data sources provided an indication of compatibility, we treated self-reported indications that the smartphone was too old to use the app *("Why haven't you downloaded the <app>?"; "My smartphone is too old, the operating system is not compatible with the app"*) as an indication of (in)compatibility for a further 54 respondents. This left outstanding 242 respondents for whom the compatibility of their Android or iPhone operating systems could not be ascertained.

App download

Android and iPhone owners were then asked *"Have you downloaded the <app>?" ("Yes", "No").*

In all survey questions about the app, the question wording referred to the relevant app for the respondent's nation of residence: in England and Wales the "NHS COVID-19" app, in

Scotland the “NHS Scotland Protect Scotland” app, and in Northern Ireland the “HSC StopCOVID NI” app.

Contact tracing settings

Those who downloaded the app were asked *“Have you turned on <IF lives in England or Wales: Contact> Tracing in the <app>?”* with the response options *“Yes, it is on all of the time”, “Yes, I always turn it on when I leave my home”, “Yes, I sometimes turn it on when I leave my home”, “Yes, but I no longer turn it on”, “No”*. For the analyses this was collapsed into a binary variable, comparing ‘Tracing on always/always when leaves home’ with ‘Tracing not always/never on’.

Household income

The monthly household net income variable was derived from the two most recent waves of the annual Understanding Society interviews, which took place between January 2017 and May 2020. Where there is a value from the most recent interview, we use that; where there is no value from that wave, we use the value from the previous interview instead. Respondents for whom household income is missing in both waves are dropped from the analysis.

Clinical risk

The variable on clinical risk was based on the NHS definition of COVID-19 clinical risk category and derived from questions about long-term health, medical treatments, pregnancy status and age (see Institute for Social and Economic Research 2021, sec. 11.7). This variable is included in the COVID-19 data sets.

Mean digital use score

For those panel members who completed the main annual survey at wave 11, we calculate a mean digital use score. This score is the mean of the respondent's responses for questions about how often they undertook eight types of digital activity (browsing, email, looking at social media, posting on social media, buying online, banking online, gaming, and streaming). The response options for each of these activities were *"Every day", "Several times a week", "Several times a month", "Once a month", "Less than once a month", "Never".* Respondents only answered these questions if they had given a substantive response to an overall internet usage question indicating they used the internet at least sometimes. We assume that respondents who answer "don't know" to any of the usage questions probably never use that type of service, so we recode "don't know" responses as "never". Where respondents skipped (declined to answer) a usage question, we impute for that question the mean score for that question for respondents who reported the same overall level of internet usage as them, excluding cases with non-substantive responses. For respondents who indicated they never used the internet or who responded "don't know" to whether they used the internet, we set the mean value as if they had responded "never" to all of the individual questions. For analysis, we round the mean scores to integer values, and present these with the same frequency labels used in the individual usage questions. For respondents who declined to answer the overall internet use question, proxy respondents at wave 11, and members of our who did not complete a Main survey at wave 11, we do not have digital use values, so we classify all of these together as cases where digital use questions were not answered.

Reasons for not using the app

For our presentation of the reasons respondents gave for not using the app, we combine certain categories, including combining values from the provided response options and the coded values from the free text entries of respondents who chose “other”. The table below details the categories that were combined.

Merged description	**Provided response options**	**Coded “other” reasons**
Have not got around to downloading it	1 Have not got around to downloading it	
Smartphone old, operating system not compatible	2 My smartphone is too old, the operating system is not compatible with the app	
I don't have storage space for the app	3 I don’t have storage space for the app	
I think the app will use up too much battery	4 I think the app will use up too much battery	
Not knowing how to download or use it inc. unable to find in app store	5 I don’t know how to download it 6 I couldn’t find it in the app store	25 Don't know how to use it/need help
I didn't know there was an app	7 I didn’t know there was an app	
Concerns about privacy or trust in government / company	8 I am worried about my privacy	15 Don't trust Government 16 Don't trust app/company
Mistrusts information or app reliability	9 I do not trust the information it provides about exposure to coronavirus	23 App is unreliable/useless/doesn't work

Taking precautions inc. not going out, another family member having the app, or using another app/method	10 I am taking precautions (e.g., social distancing, wearing a mask) so do not need the app	12 Never goes out 17 Other family member has it 26 Use an alternative app/method
Not allowed at work		13 Work won't allow it 14 Work in NHS/health/teacher so have to switch off
Doesn't want to inc. views it as unnecessary		11 Doesn't want to 19 Don't need to, not necessary
Not wanting to use Bluetooth, GPS, data allowance		20 Data usage/PAYG/only use wifi 22 Don't want to use Bluetooth/GPS
Other reasons		-9 missing -2 refusal -1 don't know 18 Don't want to have to self-isolate 21 Hardly use/carry phone 24 Not available in current location 97 Not codable