The use of QR codes to identify COVID-19 contacts and the role of data trust and data privacy

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Abstract

The aim of this paper is to provide an update on attitudes of the general public to data privacy during the COVID-19 period, as well as the factors associated with the use of QR codes and other government apps/web-sites for contact tracing purposes. We find that there has been a small decline in trust in institutions regarding data privacy since May 2020, with levels of trust still nonetheless above those reported pre-COVID. While there is a high level of self-reported use of QR codes, there are key socioeconomic, demographic, and geographic determinants of usage. Males, Aboriginal and Torres Strait Islander Australians, those born overseas in a non-English speaking country, those with low levels of education and those outside of the most advantaged areas are all less likely to use check-in apps. When we control for these background characteristics there is a very large difference in use of check-in apps based on trust in institutions. Those Australians who are more trusting in institutions with regards to data privacy are, in general, more likely to always use check-in apps – 54.2 per cent for low trust individuals compared to 68.5 per cent for high trust individuals.

1 Introduction and overview

A ubiquitous non-pharmacological strategy for attempting to reduce the spread of COVID-19 has been test-trace-isolate (TTI), particularly prior to the development of effective vaccines or when vaccination rates are too low to provide population protection. TTI means that 'extensive "testing" is used to identify cases in the community; public health agencies then "trace" the contacts of these cases in order to identify people who may have been infected; and the initial cases are asked to "isolate" and their contacts are asked to quarantine for the period of time that they could be, or become, infectious.' Grantz et al. (2021: 3).

For such a policy intervention to work, testing regimes need to be accessible and rapid. Furthermore, individuals need to be able to isolate with minimal cost to them and their community. This paper focuses on the trace element. To be able to effectively trace individuals who have been in contact with someone who has tested positive to COVID-19, it necessary to first identify people who have come in contact with a positive case. Identification of people who may not know the positive case but who have been in the same business or other physical space at the same time as a potentially infectious person has proven to be particularly challenging in all countries that have used a TTI approach.

There have been a variety of approaches for tracing (Whitelaw 2020). The simplest and first to be introduced was individuals recording their names and contact details in hard copy (paper) form. Subsequently, many countries have adapted digital tools for contact tracing, and these are one of the key components of many TTI systems (Chung et al. 2021). Such digital tools for contact tracing have predominantly utilised Bluetooth, WiFi, GPS and/or Quick Response (QR) technologies (Chen and Thio 2021; Grekousis and Liu 2021; Shahroz et al. 2021). Some GPS and Bluetooth tools are designed to be always on in the background of people's smartphones (or specially designed tags), keeping a record of other smartphones that an individual came into close proximity with. In Australia, this approach was utilised through the COVIDSafe app,[1] which unfortunately was impacted by software issues and played only a limited role in TTI. A more successful approach was utilised in Singapore through the TraceTogether app.[2]

An alternative to Bluetooth based apps are QR code-based apps, where individuals scan a code on entry to a premise (or enter a code manually) which then logs the specific time of entry (and sometimes exit). In theory, check-in can then be verified by staff on the premises, though the extent to which this occurs in practice is likely to vary substantially.[3] Countries that have relied on QR technology for contact tracing include the United Kingdom and China (Chung et al. 2021; Trestian et al. 2021), as well as Australia.[4]

Both Bluetooth/GPS and QR-code based applications require individuals to have their smartphone or alternative device with them at all times. However, where the former only requires a single download and then occasional updating (often done automatically), QR-code based apps require constant manual usage. For the system to be effective, a sufficient number of people need to use the apps with sufficient regularity (Whitelaw 2020).

[1] https://www.health.gov.au/resources/apps-and-tools/covidsafe-app
[2] https://www.tracetogether.gov.sg/
[3] https://www.canberratimes.com.au/story/7326469/act-businesses-warned-over-low-covid-check-in-levels/
[4] https://www.9news.com.au/national/coronavirus-nsw-qr-code-to-be-mandatory-at-workplaces-retail-from-july-12/86b80e20-b35d-4ac1-b712-3dadf4c4c6e7

There are a number of potential barriers to regular usage of QR-code based apps. Individuals first need to have a smartphone with sufficient connectivity and data plans. They also need to have that smartphone with them when they enter the actual premise. They need to remember to check-in and, importantly, be willing to do so. Chen and Thio (2021) explored the drivers and barriers associated with uptake of digital contact tracing apps, finding that motivation, access, technological skills and trust were key factors. Approaches or tools that can be used by governments to influence behaviour included changing behaviour norms, developing policies, marketing, and improving technology and security.

Significant privacy concerns regarding the use of data from Bluetooth-based and QR-code based apps have been raised (e.g. Greenleaf and Katharine 2020; Leins, Culnane, and Rubinstein 2020). International research suggests that the adoption of contact tracing Apps is influenced by their percieved effectiveness, previous experience with contact tracing Apps, concerns about privacy, and levels of trust in the state (Kostka and Habich-Sobiegalla 2020).

Within Australia, research indicates that in May 2020, Australians were more trusting of organisations in regard to data privacy, and less concerned about their own personal information than they were prior to the pandemic (Biddle et al. 2020). In examining the determinants of uptake of the COVIDSafe App (which has since had limited use for contact tracing), Biddle et al. (2020) found that those who had greater trust in data privacy, 55-74 year olds, and those who lived in more advantaged areas were significantly more likely to have downloaded the App. There has been limited research specifically on the uptake of QR-code based Apps. Chen et al. (2021) have examined customer cooperation regarding contract tracing, finding that cognitive trust (the rational evaluation of whether another party is trustworthy based on existing knowledge) increases people's willingness to disclose information. Furthermore, Trestian et al. (2021) have found that individuals are willing to share data in the interests of reducing the spread of COVID-19.

The aim of this paper is to understand the factors that were related to the usage of QR-code based apps in Australia at a time of moderate vaccination coverage and substantial variation by jurisdiction in the level of lockdown restrictions (mid-August 2021). At that time, Australia's two largest states (New South Wales and Victoria) were experiencing substantial lockdown restrictions. The nation's capital – Canberra – commenced lockdown during the data collection window. Apart from border restrictions, the other five states and territories had very few internal restrictions. All of Australia was closed at that time to international departures and arrivals, apart from under very limited circumstances.

We focus in particular on the role of trust in institutions regarding data privacy, as well as general confidence in government. The remainder of the paper is structured as follows. In the next section, we outline the data used in this paper. In Section 3 we provide data on the level and trends in trust in institutions regarding data privacy, with Section 4 summarising the self-reported levels and reasons for/against usage of QR-code based apps. In the final section of the results (Section 5) we analyse these two constructs together using a regression approach, with Section 6 providing some concluding comments.

2 Data used in the paper

The primary source of data for this paper is the August 2021 ANUpoll. Data from the October 2018, October 2019 and May 2020 ANUpolls are also used in this paper.

Data collection For the August 2020 ANUPoll was piloted on the 10th of August 2021. The main data collection commenced on the 11th of August and concluded on the 23rd of August. The final sample size for the survey is 3,135 respondents.[5] Of those who had completed the August 2021 survey, 76.7 per cent had completed the May 2020 survey, the last time the ANUpoll series of surveys asked respondents their views about data privacy.

The survey collected data online and through Computer Assisted Telephone Interviewing (CATI) in order to ensure representation from both the online and offline Australian population. Around 4.1 per cent of interviews were collected via CATI.

Unless otherwise stated, data in the paper is weighted to population benchmarks[6].

The ethical aspects of this research have been approved by the ANU Human Research Ethics Committee (2021/430).

3 Trust in institutions

3.1 Measures used

The October 2018, May 2020 and August 2021 ANUpolls included questions about attitudes toward data trust and data privacy. Respondents were asked: 'On a scale of 1 to 10, where 1 is no trust at all and 10 is trust completely, how much would you trust the following types of organisations to maintain the privacy of your data?'. Respondents were asked about eight types of organisations, with the order randomised. These were:

a) The Commonwealth Government in general
b) The State / Territory Government where you live
c) Banks and other financial institutions
d) Social media companies (for example Facebook, Twitter, Google)
e) Universities and other academic institutions
f) Telecommunications companies
g) Companies that you use to make purchases online
h) The Australian Bureau of Statistics

A principal components analysis suggests that a single component solution is appropriate with the Eigenvalue for the first component being 4.35 (explaining 54.4 per cent of the variation) and the second Eigenvalue being 1.23. All nine of the variables correlated at a similar level with the first component (minimum Eigenvalue of 0.29 and a maximum of 0.39). We therefore conclude that for many analysis questions, a single index with equal weights is appropriate. We therefore estimated the average value across the nine variables as our index of trust in

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[5] A total of 3,481 respondents were invited to take part in the survey, leading to a wave-specific completion rate of 90.1 per cent. Taking into account recruitment to the panel, the cumulative response rate for this survey is around 5.8 per cent.

[6] For Life in Australia™, the approach for deriving weights ly consists of the following steps:

1. Compute a base weight for each respondent as the product of two weights:
   a. Their enrolment weight, accounting for the initial chances of selection and subsequent post-stratification to key demographic benchmarks
   b. Their response propensity weight, estimated from enrolment information available for both respondents and non-respondents to the present wave.
2. Adjust the base weights so that they satisfy the latest population benchmarks for several demographic characteristics.

data privacy with a higher value of the index indicating that the individual has a higher overall level of trust in the ability of the different types of organisations to maintain their data privacy.

Respondents were asked in October 2019 to indicate the extent of agreement or disagreement with the following statements:

a) You are concerned that your online personal information is not kept secure by websites
b) You are concerned that your online personal information is not kept secure by public authorities
c) You avoid disclosing personal information online
d) You believe the risk of becoming a victim of cybercrime is increasing
e) You are able to protect yourself sufficiently against cybercrime, e.g. by using antivirus software on [reverse coded for index].

The statements were randomised, with response options of "totally agree; tend to agree; tend to disagree; and totally disagree".

Finally, respondents were asked: 'Cybercrimes can include many different types of criminal activity. How concerned are you personally about experiencing or being a victim of the following situations:

a) Identity theft (somebody stealing your personal data and impersonating you)
b) Receiving fraudulent emails or phone calls asking for your personal details (including access to your computer, logins, banking or payment information).

Response options were: very concerned; fairly concerned; not very concerned; and not at all concerned. The order in which the situation was presented to the respondent was randomised.

In order to measure the overall level of concern about the security of personal data, an index was produced which combined the seven questions on level of concern for data security and personal information (reverse coded where appropriate). The index varies from a value of 7 for those who were least concerned about personal information and data, to 28 for those who were most concerned, with an average of 21.4.

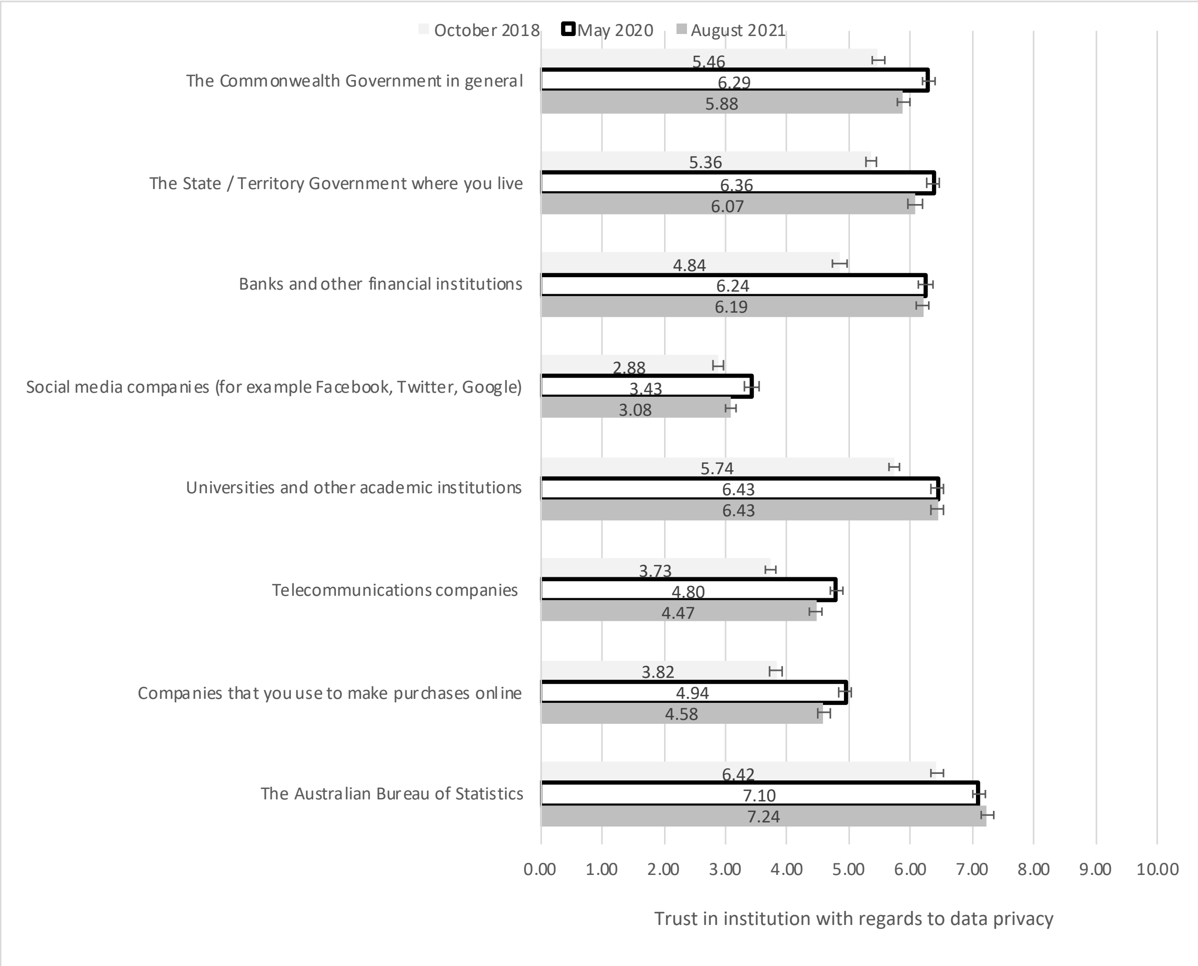
While these questions were exactly the same in the three waves of the ANUpoll, the questions leading up to them were different between waves, potentially resulting in differing priming effects. Thus some caution in interpreting changes over time is warranted, especially if the changes are only small.

3.2 Trends in trust in institutions to maintain data privacy

Following an increase in the overall level of trust in a range of types of organisations to maintain data privacy between October 2018 and May 2020 from 4.78 to 5.70, there was a decline between May 2020 and August 2021 to 5.49. Between May 2020 and August 2021 there also an increase in concern about the security of personal data and information from 20.82 to 21.40. Both these changes were statistically significant.

However, not all types of organisations/institutions experienced a decline in trust between May 2020 and August 2021. Furthermore, it should be noted that trust in all organisations/institutions was higher than pre-COVID (Figure 1). Over the most recent period, there was an increase in trust in the Australian Bureau of Statistics (potentially explained by August 2021 being a Census month with the ABS having a greater media presence), no change in trust for universities and banks, but significant decline in trust to maintain data privacy for the other five types of organisations/institutions. The biggest decline was for social media companies (a 10.1 per cent decline starting from an already low base) with large declines also observed for online companies, telecommunications companies, the Commonwealth Government; and state/territory governments.

Figure 1 Average level of trust in institutions to maintain data privacy – October 2018, May 2020, and August 2021

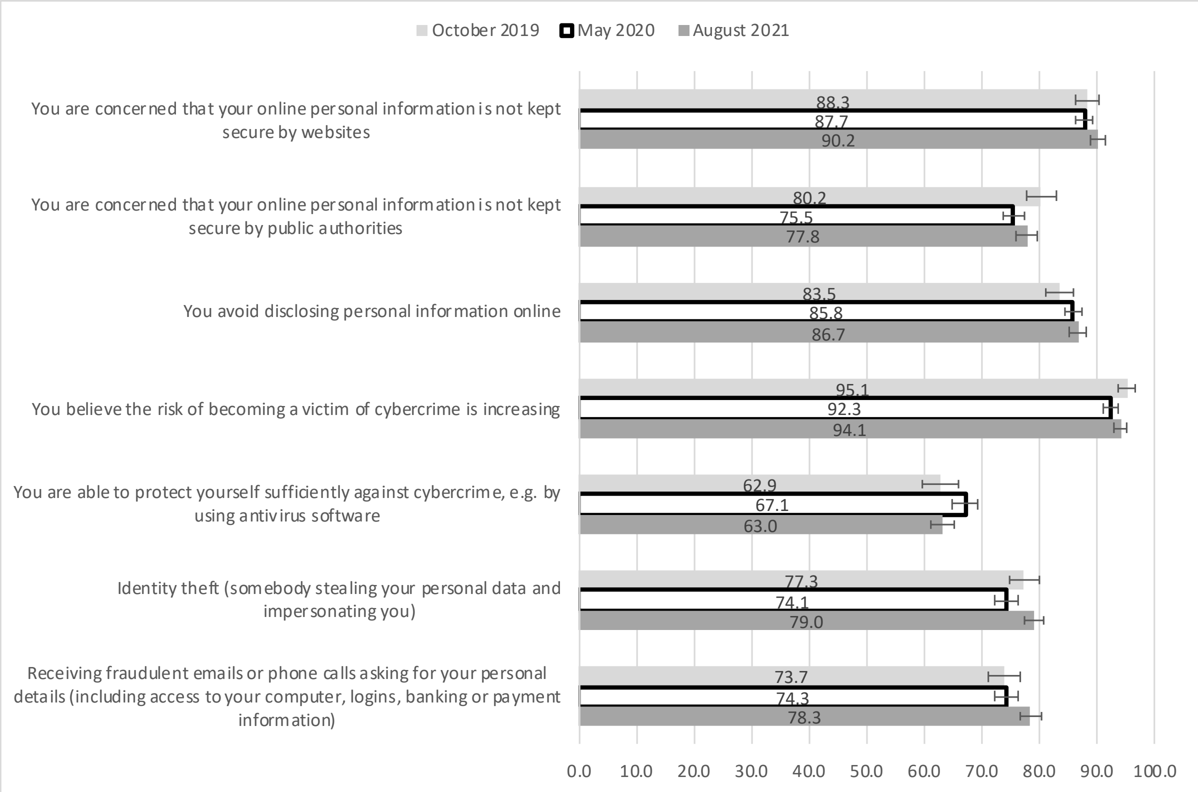


Source: ANUPoll October 2018, May 2020 and August 2021.

Figure 2 shows the proportion of Australians who are concerned about the security of their personal data and information when asked in October 2019, May 2020 and August 2021. Between October 2019 and May 2020 there was little change in the proportion of Australians who were concerned about the different potential threats to the security of their personal information and data. The main changes were a reduction in the proportion who were concerned that their online personal information is not kept secure by public authorities and an increase in being concerned about not being able to protect yourself sufficiently against cybercrime.

Keeping in mind that a higher value for the question on 'You are able to protect yourself…' indicates a lower level of concern, Figure 2 shows that there are no variables that captured a decline in concern between May 2020 and August 2021. The biggest relative increase was for the proportion of people who were concerned or very concerned about 'Identity theft (somebody stealing your personal data and impersonating you)' or 'Receiving fraudulent emails or phone calls asking for your personal details …'

Figure 2 Per cent of Australians who agreed or totally agreed that they are concerned about the security of their personal data and information, October 2019, May 2020, and August 2021



Source: ANUPoll October 2019, May 2020 and August 2021.

4 Use of QR-codes

After answering the questions on data trust and data privacy, respondents to the August 2021 ANUpoll were asked 'How frequently do you 'check in' using one of the government apps or websites when attending a business or venue that asks you to (either manually or using the QR codes).' Only 2.2 per cent of respondents answered 'Not applicable – I never attend businesses or venues that ask me to "check in"' with these individuals excluded from the remainder of the analysis. Of those who are asked to check-in: 61.9 per cent reported always; 26.3 per cent reported most of the time; 4.7 per cent reported sometimes; 3.3 per cent reported occasionally; and 3.8 per cent reported never.

While there may be some over-reporting due to people having forgotten to check-in, and hence not aware that they did not do so, as well as a degree of social-desirability bias, these reported rates of check-in are quite high.

Those respondents who reported they used QR-codes at least occasionally were asked 'What is the **main reason** you 'check in' when you do?' [bold in original]. There were four response options given, with two additional questions coded based on verbatim responses. The per cent of the relevant respondents who gave each of these reasons (in order) were:

- 32.2 per cent reported 'I want to keep myself safe';
- 26.5 per cent reported 'I want to keep others safe';
- 18.3 per cent reported 'It may help end social distancing restrictions more quickly';

- 10.7 per cent reported 'It may help the individual business or venue stay open';
- 5.6 per cent reported 'It's the law / mandatory';
- 2.9 per cent reported 'To assist contact tracing'; and
- 4.8 per cent reported another reason.

Those respondents who reported they used QR-codes less than always were asked 'What is the **main reason** you don't 'check in' when you don't do so?' [bold in original]. The per cent of the relevant respondents who gave each of the reasons (in order) were:

- 58.2 per cent reported 'I forget to do so';
- 9.8 per cent reported 'I don't have a smart phone or other device to 'check in' with';
- 7.4 per cent reported 'I don't trust the government with my data';
- 5.1 per cent reported 'I don't think it will have any benefit for me';
- 4.3 per cent reported 'I don't trust businesses with my data';
- 4.2 per cent reported 'I don't trust the safety of the apps on my smartphone';
- 2.5 per cent reported 'In a hurry/can't be bothered';
- 2.1 per cent reported 'Issues with the app/QR code';
- 1.6 per cent reported 'I don't think it will have any benefit for others'; and
- 4.8 per cent reported another reason.

5 Predictors of use of QR-codes

5.1 Socioeconomic and demographic factors

The data reported in the previous section showed that most Australians report that they check-in most or all of the time. Nonetheless, variation across the population in the use of QR codes and other forms of checking-in can highlight the population groups or areas in the country where compliance is higher or lower.

To estimate the factors associated with frequency of check-in using QR-codes, an ordered probit model is estimated. A higher value of the dependent variable represents a greater frequency of checking in using a QR Code. The first model includes demographic, socioeconomic, and geographic variables only, with positive coefficients indicating the person uses QR-codes more frequently than the base case (defined under the table), and negative coefficients indicating they check-in less frequently. The coefficient estimates are reported in Appendix Table 1.

Controlling for other characteristics, women are estimated to check-in more frequently than men and the difference is large, with 67.4 per cent of women saying they check-in always compared to 56.3 per cent of men. There are no major differences between the age groups when other demographic, socio-economic and geographic characteristics are controlled for.

According to the model estimates, Aboriginal and Torres Strait Islander Australians check-in less frequently than the non-Indigenous population. Once again, the differences are large with it being estimated that 62.1 per cent of non-Indigenous Australians saying that they check in always, compared to 50.2 per cent of Aboriginal and Torres Strait Islander Australians. The most common reason for not checking in given by Aboriginal and Torres Strait Islander respondents was 'I don't trust the government with my data', given by 34.2 per cent of respondents (substantially higher than the 7.4 per cent of the overall population who provided this response).

There were even bigger differences in frequency of check-in by country of birth. Those who were born overseas in a non-English speaking country are estimated to check-in with a much lower frequency – 49.7 per cent saying they checked in always compared to 64.7 per cent for those born in Australia or born in an English-speaking country. For those born overseas in a non-English speaking country, however, the reason for not checking in was similar to the general population, with most saying it is because they forget to do so.

There are two measures of advantage that were correlated with check-in frequency – having a university degree (and particularly a postgraduate degree) and living in a relatively advantaged area.

The final set of variables in Model 1 is the jurisdiction/area type in which the person lived. The base case category was Sydney and, given the high rates of infection in Sydney at the time, this area had the highest frequency of checking in. This was followed by Melbourne, the rest of Victoria, another capital city, and then a non-capital city outside of NSW.

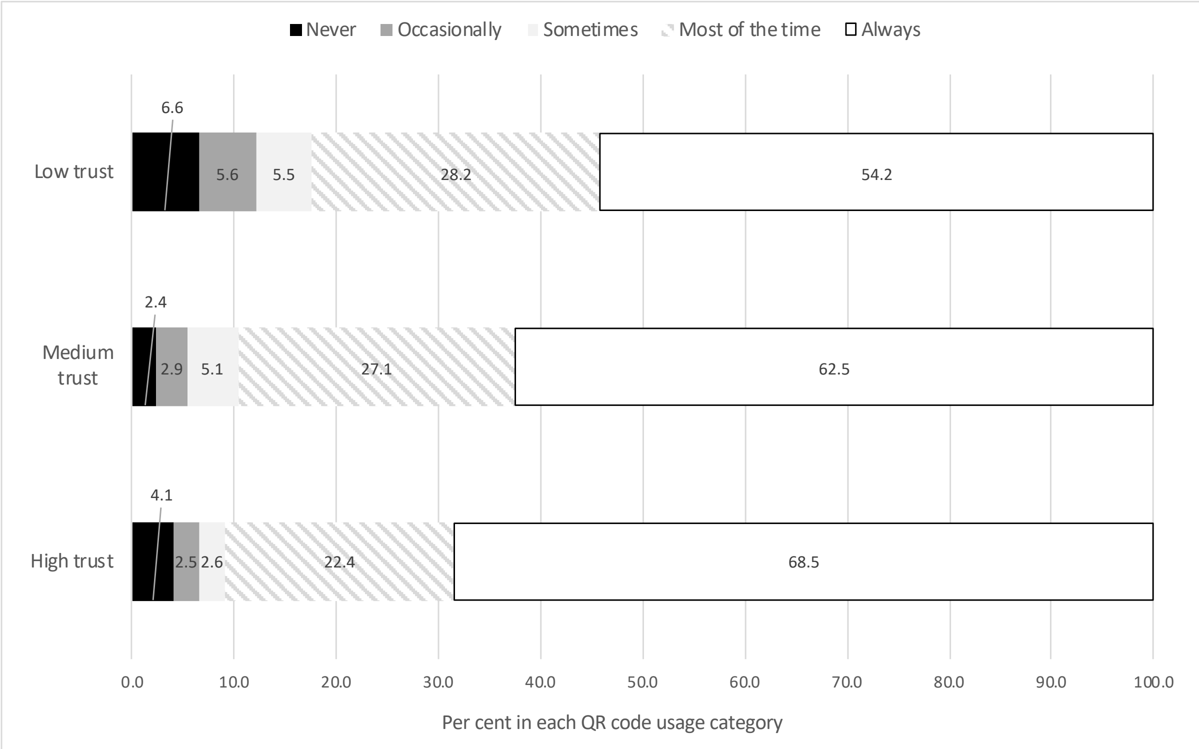
5.2 The relationship between trust in institutions and use of QR-codes

As outlined above, there is evidence from other studies that level of trust in institutions and concerns about privacy are associated with the uptake of contract tracing apps. In order to estimate the relationship between these factors and the use of QR-codes in Australia, as measured by frequency of check-in using QR-codes, three regression models have been produced. Given that the dependent variables is categories of frequency of check-in using QR-codes, an ordered probit model is used.

A regression model is estimated (Model 2, Table A2) with explanatory variables being COVID-related attitudes and the variable measuring general trust in institutions in addition to the demographic, socio-economic and geographic characteristics included in Model 1. The estimates show that there is a statistically significant relationship between an individual thinking that it is likely they will be infected by COVID-19 and having a higher frequency of usage of QR-codes.

There was no statistically significant relationship between satisfaction with the direction of the country and check-in frequency, nor was there a relationship with the concern about data breaches index. There was a much stronger relationship, however, between check-in frequency and trust in institutions regarding data. We can see the size of this relationship is quite large in simple descriptive analysis in Figure 3, which breaks the trust index down into three groups. Amongst the low-trust group (average values of 1 to 4), 54.2 per cent report that they always check-in. This rises to 62.5 per cent for those who have medium trust (average value of 4 to 7) and 68.5 per cent for those with high trust (average value of 7 to 10).

Figure 3 Frequency of check-in by trust in institutions regarding data privacy



Source: ANUpoll, August 2021.

An important finding from the econometric modelling is that individuals who have been vaccinated are (statistically) significantly and substantially more likely to use check-in codes frequently than those who have not been vaccinated. This association is estimated while holding constant fear of COVID-19 infection, which is related to vaccination status. About two-thirds (65.6 per cent) of those who had been vaccinated said that they always check-in, compared to 56.9 per cent of those who had not been vaccinated.

Although we do not include it in the model, we also find that there is a strong relationship between check-in frequency and vaccine hesitancy. Only 26.7 per cent of those who say they definitely would not get vaccinated say they always check-in. There is less of a difference between those who say they probably wouldn't get vaccinated (45.4 per cent) and those who say they probably would get vaccinated (50.0 per cent). Those who say that they definitely would get vaccinated once a vaccine is available to them have a check-in frequency that is similar to the already vaccinated (64.9 per cent). While this may not be surprising – the same factors that impact vaccine uptake are likely to impact check-in frequency – it does have real policy relevance. Particularly once restrictions have been eased, those Australians who are most at risk of COVID-19 and those most at risk of spreading to others are those who have not been vaccinated. It is this group who appears to be least likely to use the technology that provides back-up protection to vaccination.

There is a positive relationship between check-in frequency and general confidence in two particular institutions – state/territory governments, and even more so, hospitals and the health system. This latter finding is interesting because the check-in apps tend not to be managed by the health system. However, the associations suggest that the general public does not make that distinction.

The final regression model estimated (Model 3, Table A3) adds as an explanatory variable trust in data privacy for specific institutions, rather than just including the summary index. There were two specific institutions that have a positive association with check-in frequency. The first of these, State/Territory governments is not surprising, given the variation in infection rates and lockdown measures across jurisdictions, and the fact that the QR-code apps are designed and managed by State/Territory governments.

It is perhaps a bit more surprising that trust in the ABS is associated with QR-code usage. This is despite the fact that the ABS has no specific role in the check-in apps. It may reflect general trust in the data ecosystem in Australia or, for those with low trust, a belief that data from check-in apps is being shared and linked within government.

Perhaps the most interesting finding from Model 3, however, is that there is a negative relationship between trust in social media companies regarding data privacy and check-in frequency. Given the model controls for trust in other institutions, this could reflect some of the misinformation on QR-codes made available on social media and that those who trust that information from social media are less likely to have trust in a government app.

6 Concluding comments

Test-Trace-Isolate has been one of the main non-pharmacological responses to the COVID-19 pandemic, utilised to varying degrees in most middle- and high-income countries. The extent to which requirements have been enforced has varied based on the level of the virus circulating in the community, as well as the level of vaccination amongst the population. At the time of writing, there were some countries that were still heavily reliant on TTI, with others substantially reducing their usage, particularly for countries with high vaccination rates. Usage may resume, however, with new strains of the virus or if vaccine protection wanes.

In Australia TTI has been used extensively and, along with border restrictions, has seen a very low rate of infection, hospitalisation, and mortality from COVID-19. In this paper, we have shown that there are key socioeconomic, demographic, and geographic determinants of one aspect of TTI – the use of government apps or websites to check-in when attending a business or venue. Males, Aboriginal and Torres Strait Islander Australians, those born overseas in a non-English speaking country, those with low levels of education and those outside of the most advantaged areas are all less likely to use check-in apps.

However, we also show that when we control for these background characteristics there is a very large difference in use of check-in apps based on trust in institutions and concerns for data privacy. This aligns with previous literature that highlights the importance of trust in institutions and concerns for data privacy (Biddle et al. 2020; Kostka and Habich-Sobiegalla 2020; Praveen and Ittamalla 2020). Those Australians who are more trusting in institutions with regards to data privacy are, in general, more likely to always use check-in apps – 54.2 per cent for low trust individuals compared to 68.5 per cent for high trust individuals. One exception to this general association is that those who have high trust in social media with regards to data privacy (and presumably high trust with information or misinformation on social media) are less likely to use check-in codes.

In general, the analysis presented in this paper shows that there are clear costs in terms of the ability to implement TTI policies of any policy initiatives that may reduce trust in institutions with regards to data privacy. This may include the use of data from the check-in apps specifically, but also broader data policy.

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Appendix 1 Regression tables

Table A1 Demographic, socioeconomic and geographic factors associated with check-in frequency – ordered probit model, August 2021

Explanatory variables	Coeff.	Signif.
Female	0.239	***
Aged 18 to 24 years	0.078	
Aged 25 to 34 years	0.030	
Aged 45 to 54 years	0.130	
Aged 55 to 64 years	0.036	
Aged 65 to 74 years	0.174	*
Aged 75 years plus	-0.156	
Indigenous	-0.344	*
Born overseas in a main English-speaking country	0.057	
Born overseas in a non-English speaking country	-0.291	***
Speaks a language other than English at home	-0.132	
Has not completed Year 12 or post-school qualification	-0.074	
Has a post graduate degree	0.271	***
Has an undergraduate degree	0.174	**
Has a Certificate III/IV, Diploma or Associate Degree	0.049	
Lives in the most disadvantaged areas (1st quintile)	0.040	
Lives in next most disadvantaged areas (2nd quintile)	0.050	
Lives in next most advantaged areas (4th quintile)	-0.021	
Lives in the most advantaged areas (5th quintile)	0.155	*
Lives in non-capital city NSW	0.036	
Lives in Melbourne	-0.188	**
Lives in non-capital city Victoria	-0.214	
Lives in another non-capital city	-0.436	***
Lives in another capital city	-0.282	***
Cut-point 1	-1.845	
Cut-point 2	-1.521	
Cut-point 3	-1.221	
Cut-point 4	-0.296	
Sample size	2,940	

Source: ANUpoll, August 2021

Notes: Ordered Probit Regression Model. The base case individual is male; aged 35 to 44 years; non-Indigenous; born in Australia; does not speak a language other than English at home; has completed Year 12 but does not have a post-graduate degree; lives in neither an advantaged or disadvantaged suburb (third quintile); and lives in Sydney.

Coefficients that are statistically significant at the 1 per cent level of significance are labelled ***; those significant at the 5 per cent level of significance are labelled **, and those significant at the 10 per cent level of significance are labelled *.

Table A2 Attitudinal, demographic, socioeconomic and geographic factors associated with check-in frequency – ordered probit model, August 2021

Explanatory variables	Coeff.	Signif.
Thinks it likely to be infected by COVID-19 in next 6 months	0.095	
Satisfied with direction of country	0.081	
Index of trust in institutions regarding data privacy	0.041	**
Index of data breach concerns	0.011	
Received a COVID-19 vaccine	0.264	***
Generalised confidence (as of April) in Commonwealth Government	-0.090	
Generalised confidence (as of April) in public service	0.013	
Generalised confidence (as of April) in state/territory governments	0.128	*
Generalised confidence (as of April) in hospitals and the health care system	0.208	***
Generalised confidence (as of April) in police	0.014	
Female	0.213	***
Aged 18 to 24 years	0.160	
Aged 25 to 34 years	0.022	
Aged 45 to 54 years	0.005	
Aged 55 to 64 years	-0.146	
Aged 65 to 74 years	-0.005	
Aged 75 years plus	-0.385	***
Indigenous	-0.322	
Born overseas in a main English-speaking country	0.044	
Born overseas in a non-English speaking country	-0.421	***
Speaks a language other than English at home	-0.082	
Has not completed Year 12 or post-school qualification	-0.020	
Has a post graduate degree	0.052	
Has an undergraduate degree	0.003	
Has a Certificate III/IV, Diploma or Associate Degree	-0.030	
Lives in the most disadvantaged areas (1st quintile)	0.033	
Lives in next most disadvantaged areas (2nd quintile)	-0.033	
Lives in next most advantaged areas (4th quintile)	-0.099	
Lives in the most advantaged areas (5th quintile)	0.013	
Lives in non-capital city NSW	0.049	
Lives in Melbourne	-0.156	
Lives in non-capital city Victoria	-0.251	*
Lives in another non-capital city	-0.367	***
Lives in another capital city	-0.210	**
Cut-point 1	-1.297	
Cut-point 2	-0.925	
Cut-point 3	-0.622	
Cut-point 4	0.393	
Sample size	2,472	

Source: ANUpoll, August 2021

Notes: Ordered Probit Regression Model. The base case individual is male; aged 35 to 44 years; non-Indigenous; born in Australia; does not speak a language other than English at home; has completed Year 12 but does not have a post-graduate degree; lives in neither an advantaged or disadvantaged suburb (third quintile); and lives in Sydney.

Coefficients that are statistically significant at the 1 per cent level of significance are labelled ***; those significant at the 5 per cent level of significance are labelled **, and those significant at the 10 per cent level of significance are labelled *.

Table A3 Relationship between trust in institutions regarding data privacy and check-in frequency, controlling for demographic, socioeconomic and geographic factors – ordered probit model, August 2021

Explanatory variables	Coeff.	Signif.
The Commonwealth Government in general	-0.021	
The State / Territory Government where you live	0.045	**
Banks and other financial institutions	0.020	
Social media companies (for example Facebook, Twitter, Google)	-0.035	**
Universities and other academic institutions	0.008	
Telecommunications companies	-0.001	
Companies that you use to make purchases online	-0.010	
The Australian Bureau of Statistics	0.048	***
Female	0.243	***
Aged 18 to 24 years	0.086	
Aged 25 to 34 years	0.012	
Aged 45 to 54 years	0.094	
Aged 55 to 64 years	-0.019	
Aged 65 to 74 years	0.092	
Aged 75 years plus	-0.288	**
Indigenous	-0.310	
Born overseas in a main English-speaking country	0.044	
Born overseas in a non-English speaking country	-0.294	***
Speaks a language other than English at home	-0.107	
Has not completed Year 12 or post-school qualification	0.028	
Has a post graduate degree	0.250	**
Has an undergraduate degree	0.136	
Has a Certificate III/IV, Diploma or Associate Degree	0.048	
Lives in the most disadvantaged areas (1st quintile)	0.059	
Lives in next most disadvantaged areas (2nd quintile)	0.067	
Lives in next most advantaged areas (4th quintile)	-0.026	
Lives in the most advantaged areas (5th quintile)	0.135	
Lives in non-capital city NSW	0.033	
Lives in Melbourne	-0.200	**
Lives in non-capital city Victoria	-0.216	
Lives in another non-capital city	-0.446	***
Lives in another capital city	-0.281	***
Cut-point 1	-1.414	
Cut-point 2	-1.074	
Cut-point 3	-0.765	
Cut-point 4	0.189	
Sample size	2,910	

Source: ANUpoll, August 2021

Notes: Ordered Probit Regression Model. The base case individual is male; aged 35 to 44 years; non-Indigenous; born in Australia; does not speak a language other than English at home; has completed Year 12 but does not have a post-graduate degree; lives in neither an advantaged or disadvantaged suburb (third quintile); and lives in Sydney.

Coefficients that are statistically significant at the 1 per cent level of significance are labelled ***; those significant at the 5 per cent level of significance are labelled **, and those significant at the 10 per cent level of significance are labelled *.