An evaluation of the population uptake and contact tracer utilisation of the Covid-19 Bluetooth Exposure Notification Framework in New Zealand

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Abstract

Objective: Our primary research objective was to assess the population uptake and contact tracer utilisation of the Bluetooth function of the New Zealand Covid Tracer App (NZCTA) throughout the pandemic.

Methods: We adopted a retrospective cohort study design using all diagnosed COVID-19 community cases from December 12, 2020 to February 16, 2022.

Results: At its height, more than 60% of the eligible population had the Bluetooth function of NZCTA activated. However, only an estimated 2.2% of the population was able to fully participate. Cases managed by the national case investigation service were 17 times (aRR 17.54, 95%CI: 13.02-23.90) and 9 times (aRR 9.27, 95%CI: 6.91, 12.76) more likely to generate a Bluetooth token than cases managed by local public health units during the Delta and Omicron periods, respectively.

Conclusions: The Bluetooth functionality of the NZCTA likely had a low impact on the pandemic response in NZ despite its exceptionally high levels of public uptake. The primary reason for the lack of impact was the low utilisation by contact tracers.

Implications for public health: The results highlight the need for greater consultation and collaboration with the public health sector during the development and implementation of digital contact tracing tools.

Key words: COVID-19, digital contact tracing, Bluetooth, exposure notification framework, health equity

Introduction

Contact tracing is a key public health response measure to control infectious diseases, including SARS-CoV-2 (which causes COVID-19). In Aotearoa New Zealand (NZ), COVID-19 required transformational change in the contact tracing system, including the introduction of a digital contact tracing (DCT) mobile phone application, the New Zealand Covid Tracer App (NZCTA) (see Supplementary Material for a full overview of the DCT developments in NZ).

In December 2020, a Bluetooth proximity detection system based on the Apple/Google Exposure Notification Framework (ENF) was added to NZCTA. This system used Bluetooth to exchange privacy-preserving identification keys wirelessly between enabled smartphones, maintaining a log of times when each key was heard.[1] If a user tested positive for COVID-19, contact tracers could ask them to upload their keys, which would then be broadcast to all devices, checked locally on each device for matches, and notify any user that they may have been exposed to the disease as a contact of the case.

Importantly, this approach only required users to enable it, and then it would run passively in the background. The ENF system was used in many other jurisdictions, and the NZCTA system was built from open-source code from Ireland's implementation (COVID Green). Notably, the proximity detection system used in NZ was different from the one used in nearby jurisdictions Singapore and Australia, which adopted a centralised approach.

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The data lived on the device and was not automatically transferred to public health officials. If a person tested positive, then they could be given tokens to enter into NZCTA, which would then release that data, which would go to a Ministry of Health server that would automatically distribute that data to other devices without human intervention.

There have been assessments of the effectiveness of national Bluetooth DCT technologies in many jurisdictions, including Switzerland,[2,3] Australia,[4] Spain,[5] the United Kingdom,[6–8] Norway,[9] Qatar,[10] USA[11] and Finland[12] with varying results. For example, one evaluation in England and Wales estimated the app alone averted 1 million cases (sensitivity analysis 450,000–1,400,000), 44,000 hospitalisations and 9,600 deaths in its first year.[7] In contrast, over a six-month period, Australia's COVIDSafe app was only used by 22% of cases, resulting in an estimated <0.1% increase in the identification of clinically relevant close contacts not already identified by the manual process.[4]

The majority of DCT evaluation studies have focused on the potential barriers and facilitators to public adoption of these tools.[13–17] Modelling and empirical studies have demonstrated that the efficacy of these tools is highly dependent on public coverage.[4,18] In NZ, three evaluations of NZCTA have focused on public uptake[19–22] and evaluations of small pilot studies.[23–25] However, limited research has focused on public health sector adoption of these tools internationally, which is a strong determinant of the potential effectiveness of these tools. One study of the SwissCovid app suggests compliance from health officials was high (eg > 90%).[26] However, in NZ, there was a documented reluctance from public health officials to adopt DCT tools[25] as well as other digital solutions developed for the end-to-end contact tracing process.[27,28]

Given the privacy-preserving nature of Bluetooth proximity apps, one approach to assess their implementation, and thus their effectiveness, has been to focus on the notification cascade. The notification cascade is the series of steps that have to occur from case identification to contact action. The notification cascade has been assessed in the context of the Swiss Bluetooth proximity app, SwissCovid.[2,3,26,29] Key steps along the cascade include public uptake; contact tracer uptake; case provision of data once prompted; contact receiving a notification and contact acting on a notification (more detail is provided in the methods and results sections). More steps along the cascade introduce greater potential for reductions in effectiveness, so it is important to measure these steps to ensure a valid evaluation.

Our primary research objective was to assess the nature and extent of the population uptake and contact tracer utilisation of Bluetooth function of NZCTA throughout the pandemic.

Methods

Study design

This study has two main components. The first was a retrospective cohort study design using all diagnosed COVID-19 community cases (excluding cases isolated at the border within managed quarantine facilities). Data used were from any diagnosed COVID-19 cases aged 15+ in NZ stored in the National Contact Tracing Solution (NCTS), a centralised IT platform developed in 2020 to support the end-to-end contact tracing process. Our observation period started from December 12, 2020 (the date Bluetooth was introduced to NZCTA) to February 16, 2022 (which marked the effective end for the elimination/suppression phase of the NZ Covid-19 response and transition to a mitigation response with the majority of contact tracing switching to a self-service model after that date e.g. completed by cases rather than public health officials).

The second component was a descriptive analysis of key notification cascade metrics, as described below.

Data sources

Contact tracing data were sourced from Manatū Hauora (the Ministry of Health). This research uses three main datasets. First, the National Contact Tracing Solution (NCTS) data includes anonymised information about all community COVID-19 cases in NZ at the individual-level, including information on case ethnicity, age, sex and contact tracing organisation responsible for the case. Second, NZCTA usage data provided information on the number of devices in NZ with the Bluetooth functionality activated. Third, the NZ COVID outbreak report provided information on NZCTA notification counts on a daily basis (a full data dictionary is provided in Supplementary Material).

Cohort study outcome

The primary outcome for our analysis was *Bluetooth token generation* as a binary outcome. Token generation indicated that a case was given the opportunity to provide DCT data by entering the token/code into NZCTA, which would release the data (keys) to the central server, but does not guarantee that the data were provided or that contacts were found or notified.

Cohort study covariates investigated

Data from NCTS included case demographics, including age, sex and ethnicity. For age, we classified age into four categories: 15–24; 25–44; 45–59; 60+. Ethnicity was prioritised ethnicity, meaning a case was allocated to a single ethnic group in order of priority: Māori (NZ Indigenous population), Pacific, Asian and European/Other.

NCTS data also indicated the contact-tracing organisation responsible for handling the case. Initially, contact tracing was managed by 12 local Public Health Units (PHUs). Increasing case volumes associated with the Delta outbreak led to the National Case Investigation Service (NCIS) being established in November 2021.[30] NCIS contracted a call centre that specialises in health research to conduct contact tracing in November 2021. NCIS call centre staff were provided with training and a script to support contact tracing, including standard operating procedures (SOPs) around NZCTA uploads. A key distinction is that NCIS call centre staff were not necessarily clinically trained, and therefore did not exercise clinical judgement in contact tracing decisions, and were more likely to follow the scripts and SOPs provided. In our analysis, we collapsed all PHUs into a single category, but the majority of the cases were handled by the Auckland Regional Public Health Service (ARPHS) due to the majority of cases appearing in Auckland. Notification cascade metrics.

To estimate public uptake, we used the peak usage of the Bluetooth system of NZCTA, divided by the total population aged 15+. To estimate contact tracer uptake of Bluetooth functionality, we divided the percentage of cases that had a Bluetooth token generated for all PHUs (our estimate for public health official compliance) by the percentage of cases with a token for NCIS (our estimate for complete compliance because staff followed a script rather than clinical judgement). In this context, we define uptake as a conscious action of a user to take up or use something that is available. As mentioned, NCIS staff were required to follow a script when conducting contact tracing, which included a prompt to ask a case for their Bluetooth data. Consequently, we assume near 100% compliance from contact tracers from NCIS. In contrast, PHU staff were provided the opportunity to apply their clinical judgement during this process, which means they were not mandated to request this information from cases.[31] There may be other issues that may have led to a case not uploading their token (e.g. technical software issue), but these issues were likely to impact PHU and NCIS staff equally. To estimate the proportion of cases that uploaded their data once being provided a token, we divided the total number of devices sending out a notification by the total number of tokens generated across the study period. For the likelihood of a contact receiving a notification and a contact acting on the notification we have had to rely on international evidence as there was no reliable way to determine these metrics with the data available in NZ. In this case, we have used evidence from the SwissCovid app, which indicated 58%[26] and 51%[3,29] (average of two papers), respectively.

Analytic phases of the pandemic

We conducted our analyses separately for three time periods: 1) Pre-Delta: December 12, 2020 to August 16, 2021; 2) Delta wave: August 17, 2021 to January 6, 2022; 3) Omicron wave: January 7, 2022 to February 16, 2022.

Statistical analysis

We used a modified Poisson regression to estimate the effects of each predictor on Bluetooth token generation.[32] A purposeful selection of covariates was used to develop initial multiple regression models.[33,34] Full models were populated with all significant predictors ($p<0.1$) from the univariate models and backwards elimination using Akaike's Information Criterion (AIC) was used to help select the final model.[35]

We calculated adjusted relative risks (a*RR*) and their respective 95% confidence intervals (CI) for each included predictor in the multivariable models. All analyses were performed in R (R-Project. www.r-project.org).

Results

Cohort study participants

Table 1 shows the characteristics of the COVID-19 cases included in our retrospective cohort. Overall, Māori and Pacific people were over-represented in case numbers during the pre-Delta and Delta phases, as well as overall compared to their population distribution. Asian cases were overrepresented during the Omicron phase, while other ethnicity cases were underrepresented across each period and overall. PHUs handled the most cases overall (61.4%), which was predominat during the pre-Delta (100%) and Delta (89.7%) phases. In the Omicron phase, NCIS took over as the responsibility for the majority of case investigation and contact tracing (75.8%).

Uptake in relation to public health agency and participant characteristics

Table 2 shows the results from a logistic regression model of differences in Bluetooth token generation in the Delta and Omicron periods by ethnicity, age, sex and contact tracing organisation. Contact tracing organisation allocation was a major driver of the likelihood of generating a Bluetooth token, with those cases handled by NCIS being 17.54 (95%CI: 13.02, 23.90) and 9.27 (95%CI: 6.91, 12.76) times more likely to be given a token than those cases handled by PHUs during the Delta and Omicron periods, respectively. The impact of contact tracing organisation allocation can also be seen in the differences in rate ratios by ethnicity between the Delta (primarily handled by ARPHS) and Omicron (primarily handled by NCIS) periods (see Supplementary Table 1 for descriptive statistics of Bluetooth token generation by PHU and NCIS by ethnicity).

Table 1: Retrospective cohort of COVID-19 cases in New Zealand from December 2020 to February 2022.

Characteristics	Total		Pre-Delta		Delta		Omicron	
	N	(%)	N	(%)	N	(%)	N	(%)
All	13803	(100)	21	(0.2)	7820	(56.7)	5962	(43.2)
Sex								
Female	6991	(50.6)	13	(61.9)	3913	(50.0)	3065	(51.4)
Male	6804	(49.3)	8	(38.1)	3903	(49.9)	2893	(48.5)
Missing	8	(0.1)	0	(0.0)	4	(0.1)	4	(0.1)
Age								
15–24	3730	(27.0)	6	(28.6)	2036	(26.0)	1688	(28.3)
25–44	6363	(46.1)	4	(19.0)	3674	(47.0)	2685	(45.0)
45–59	2598	(18.8)	11	(52.4)	1473	(18.8)	1114	(18.7)
60+	1112	(8.1)	0	(0.0)	637	(8.1)	475	(8.0)
Ethnicity								
Māori	3982	(28.8)	1	(4.8)	3280	(41.9)	701	(11.8)
Pacific	4681	(33.9)	4	(19.0)	2326	(29.7)	2351	(39.4)
Asian	2019	(14.6)	14	(66.7)	475	(6.1)	1530	(25.7)
Other	2967	(21.5)	2	(9.5)	1688	(21.6)	1277	(21.4)
NA	154	(1.1)	0	(0.0)	51	(0.7)	103	(1.7)
Contact tracing organisation								
Public health unit	8475	(61.4)	21	(100.0)	7011	(89.7)	1443	(24.2)
National case investigation service	5328	(38.6)	0	(0)	809	(10.3)	4519	(75.8)

Table 2: Logistic regression model of Bluetooth token generation in the Delta and Omicron periods by sociodemographic characteristics and contact tracing organisation.

Characteristic	Delta				Omicron			
	Total cases	Token generated	Crude estimate	Adjusted estimate[a]	Total cases	Token generated	Crude estimate	Adjusted estimate[a]
	N	n (%)	RR (95% CI)	aRR (95%CI)	N	n (%)	RR (95% CI)	aRR (95%CI)
All	7820	260 (3.3)	-	-	5962	1526 (25.6)	-	-
Ethnicity								
Māori	3280	34 (1.0)	Ref	Ref	701	45 (6.4)	Ref	Ref
Pacific	2326	41 (1.8)	**1.70 (1.08-2.69)**	**1.61 (1.02-2.56)**	2351	470 (20.0)	**3.11 (2.32-4.29)**	0.95 (0.70-1.33)
Asian	475	84 (17.7)	**17.06 (11.57-25.73)**	**5.18 (3.43-7.97)**	1530	569 (37.2)	**5.79 (4.33-7.96)**	**1.73 (1.27-2.42)**
Other	1688	97 (5.7)	**5.54 (3.79-8.31)**	**2.54 (1.71-3.85)**	1277	408 (31.9)	**4.98 (3.70-6.86)**	**1.75 (1.28-2.45)**
NA	51	4 (–)	–	–	103	34 (–)	–	–
Age								
15–24	2036	49 (2.4)	Ref	Ref	1688	377 (22.3)	Ref	Ref
25–44	3674	137 (3.7)	**1.55 (1.13-2.17)**	1.15 (0.84-1.62)	2685	834 (31.1)	**1.39 (1.23-1.57)**	**1.29 (1.14-1.47)**
45–59	1473	50 (3.4)	**1.41 (0.95-2.09)**	1.04 (0.69-1.55)	1114	262 (23.5)	1.05 (0.90-1.23)	1.00 (0.85-1.17)
60+	637	24 (3.8)	1.57 (0.95-2.52)	0.94 (0.56-1.53)	475	53 (11.2)	**0.50 (0.37-0.66)**	**0.49 (0.36-0.64)**
Sex								
Male	3903	116 (3.0)	Ref	Ref	2893	744 (25.7)	Ref	Ref
Female	3913	144 (3.7)	1.24 (0.97-1.58)	**1.45 (1.13-1.86)**	3065	782 (25.5)	0.99 (0.90-1.10)	1.06 (0.96-1.17)
Unknown	4	0 (0.0)	–	–	4	2 (–)	–	–
Contact tracing organisation								
Public health unit	7011	64 (<1.0)	Ref	Ref	1443	47 (3.3)	Ref	Ref
National case investigation service	809	196 (24.2)	**26.54 (20.14-35.45)**	**17.54 (13.02-23.90)**	4519	1479 (32.7)	**10.05 (7.61-13.62)**	**9.27 (6.91-12.76)**

Bolded values are statistically significant at $p<0.05$.
[a]Mutually adjusted for ethnicity, age, sex and public health unit.

During the Delta period, Pacific, Asian and cases of other ethnicities were 1.61 (95%CI: 1.02, 2.56), 5.18 (95%CI: 3.43, 7.97) and 2.54 (95% CI: 1.71, 3.85) times more likely to be given a Bluetooth token compared to Māori cases, adjusting for age, sex and contact tracing organisation allocation. During the Omicron period, these differences substantially reduced to 0.95 (95%CI: 0.70, 1.33), 1.73 (95%CI: 1.27, 2.42) and 1.75 (95%CI: 1.28, 2.45) for Pacific, Asian and Other ethnicities, respectively. Across all ethnicities, Bluetooth token generation during Delta was low (between 1.0% for Māori and 17.7% for Asian), compared to Omicron (between 6.4% for Māori and 37.2% for Asian).

Once adjusted for sex, ethnicity and contact tracing organisation, there were no statistically significant differences by age during Delta. During Omicron, cases aged 25-44 were more likely to generate a token than cases aged 15-24 (aRR 1.29, 95%CI: 1.14, 1.47) while cases aged 60+ were less likely to generate a token than cases aged 15-24 (aRR 0.49, 95%CI: 0.36, 0.64). Women were 1.45 times (95%CI: 1.13, 1.86) more likely to be given a Bluetooth token than men, but only during Delta. Supplementary Table 2 and Supplementary Figure 1 show the Bluetooth tokens generated by case sociodemographic characteristics and contact tracing allocation throughout the pandemic.

Notification cascade metrics

At peak usage of NZCTA during December 2021, around 2.4 M devices were participating in Bluetooth tracing. Public uptake was around ~35% pre-Delta and rose to a height of 61.7% during the Delta outbreak (2.4 M/4 M) (see Supplementary Figure 1). Table 3 shows the notification cascade steps with the primary actor, actions taken and estimates for compliance derived from a combination of observed values in New Zealand and evaluations of the SwissCovid App with comparisons of the New Zealand and Swiss populations age 15 and over after each step. In New Zealand, at its height, 61.7% of the population had Bluetooth activated on their device, giving a total accessible population of 2.5 million people (a 38.3% reduction from the total eligible population). By far the largest impact was contact tracer uptake, which we estimated at 4.1% (1.3% cases handled by PHUs had Bluetooth tokens compared to 31.4% for our NCIS 'ground truth'). This low uptake reduced the total pool of people to 92,600 (2.2% of the eligible population), representing a 95.9% reduction from the previous step in the cascade. From this point, the subsequent steps were significantly impaired with a final population of 27,400 (0.7% of the eligible population) being served. If contact tracer uptake was increased to 95% (through stronger compliance with SOPs), the final number of people fully participating in the system would have been 634,700 or 15.3% of the population (23 times more than the observed estimate).

Discussion

Our study has demonstrated that the Bluetooth functionality of the NZCTA was widely adopted by the public but not by contact tracers. Consequently, our notification cascade estimated that <1% of the population was eligible for full participation for cases handled by PHUs. There were stark inequities in participation by ethnicity, with Māori having substantially lower rates of participation than Asian, Pacific and other ethnicities. These inequities were in large part driven by differential uptake of the Bluetooth system by contact tracers at PHUs compared to at NCIS.

The public uptake of the NZCTA Bluetooth functionality was one of the largest successes of the DCT experience in NZ. A public uptake of

Table 3: Notification cascade steps with the primary actor, actions taken and estimates for compliance derived from a combination of observed values in New Zealand and evaluations of the SwissCovid App.

Notification cascade steps	Primary actor	Action taken	Estimates of compliance for each step[a]		Cumulative impact on effective population uptake after step[b]	
			New Zealand NZCTA	Switzerland SwissCovid App	New Zealand NZCTA[c]	Switzerland SwissCovid App[d]
Public uptake	The public (cases and contacts)	Members of the public were required to: 1) Download an app; 2) Enable the bluetooth functionality; 3) Carry their phones with them.	61.7% (observed)	26% (Daniore 2022)[2]	61.7% (1.00*0.617 = 0.617) population = 2,566,600	26% (1.00*0.26 = 0.26) population = 1,906,295
Contact tracer uptake	Contact tracers	When interviewing a case, contact tracers were required to prompt the case and provide an opportunity for the case to upload their unique keys to notify the server and broadcast to other devices.	2.5% (observed)	94% (Ballouz, 2022)[26]	2.5% (0.617*0.041 = 0.025) population = 105,200	24% (0.26*0.94 = 0.24) population = 1,791,918
Case provision of data	The public (cases only)	Upon being prompted, a case provided their keys to be broadcast to other devices.	88% (observed)	77% (Average of menges, 2021[3] = 60% and ballouz, 2022[26] = 93%)	2.2% (0.025*0.88 = 0.022) population = 92,600	18% (0.24*0.77 = 0.18) population = 1,379,777
Contact receiving a notification	The public (contacts only)	Once a match is detected via the app between a case and contact, the contact receives a notification about their potential exposure to COVID-19.	58% (ballouz, 2022)[26]	58% (ballouz, 2022)[26]	1.3% (0.022*0.58 = 0.013) population = 53,700	9% (0.18*0.58 = 0.09) population = 800,270
Contact acting on a notification	The public (contacts only)	Once a contact receives a notification about their exposure to COVID-19, they adjust their behaviour accordingly (e.g. self-isolation, test, monitoring for symptoms etc).	51% (ballouz, 2021 & ballouz 2022)[26,29]	51% (ballouz, 2021 & ballouz 2022)[26,29]	0.7% (0.013*0.51 = 0.007) population = 27,400	5% (0.09*0.51 = 0.03) population = 408,138

[a]Derived from observations in this current paper or evaluations of the SwissCovid app.
[b]Where the effective population uptake after step = (proportion of the population remaining from previous cascade step) * (estimate of compliance for the current cascade step),
[c]Using the 2018 population aged 15 and over, n=4,160,129,
[d]Using the 2018 population aged 15 and over 7,331,906,

~60% at its height was substantially higher than estimates from Switzerland (26%),[2] Australia (20%),[36] Spain (33%)[5] and United Kingdom (29%)[7] using similar systems. Previous work in NZ highlighted that high levels of trust in the NZ government contributed to individuals' uptake of the NZCTA.[19,22] Public trust in the NZ government's COVID-19 response was reinforced by the successful elimination strategy that led to very low numbers of COVID-19 cases in the community until the arrival of the Delta variant in August 2021, while the majority of the world faced overwhelmed health systems and lockdowns.[37]

The results indicate that there was a level of baseline inequity by ethnicity in participation in the system. For example, even after adjusting for age, sex and PHU allocation, Māori and Pacific were still between one and five times less likely to receive a token in the Bluetooth system than other ethnicities. This baseline inequity can be partly (but not fully) explained by differences in digital inclusion between Māori and Pacific compared to other ethnicities.[38] Interestingly, Asian participation was substantially higher than all other ethnicities. Previous work in NZ has observed greater compliance with COVID-19 response measures (e.g. mask wearing) among the Asian population compared to other ethnicities,[39,40] which is reflected in other Euro-centric countries.[41–43] Compliance with COVID-19 response measures was higher in Asian countries than their Western counterparts.[44,45] The higher compliance has been attributed to greater awareness of public health and social responsibilities as a result of responses to SARS and MERS outbreaks.[45]

Unfortunately, the existing inequities in participation by ethnicity were exacerbated by contact tracers' reluctance to use the data. The crude rates show that Māori were between one and 16 times less likely to receive a token in the Bluetooth system compared to other ethnicities, with the difference between the crude and adjusted rates largely driven by contact tracing allocation. The initial case triage system used by PHUs involved moving all cases of lower priority (e.g. non-Māori, non-Pacific) to NCIS, which led to over-representation of Māori and Pacific cases handled by PHUs. The ethnicity-prioritised triaging system may have provided a higher standard of overall care to Māori and Pacific cases through their direct interaction with clinically trained staff at PHUs (its intended purpose). However, in the case of the DCT data, this difference led to substantial inequities in access to the Bluetooth DCT system. Supplementary Table 1 showed that Māori assigned to PHUs had a token generation rate of 0.5% (20/3688) compared to 20.1% (59/293) for Māori assigned to NCIS.

The causes of differential performance for Māori by contact-tracing organisations cannot be directly explained within the current study. One potential driver could have been an institutional reluctance to utilise these tools by staff at PHUs. One NZ study in 2020 with contact tracers and policy professionals highlighted concerns about the use of DCT as a tool to aid contact tracing.[25] At that time, there was consensus that there should be minimal or no application of the DCT data to identify or notify close contacts, which was an opinion shared in other jurisdictions.[4] Another potential contributor for the differential performance for Māori could be the well documented impacts of a health system that systemically prioritises the health of other ethnicities over Māori.[46] This discrimination includes evidence of implicit and explicit racial bias against Māori at the individual level from health professionals.[47,48]

Our notification cascade highlights that the NZCTA likely had a negligible impact on the epidemic curve in NZ with an estimated <1% of population being eligible for full participation. Modelling and empirical studies have shown that public uptake is crucial to the efficacy of DCT tools.[7,18] The focus on public uptake has often de-emphasised the other challenges of implementing DCT tools that are brought to light by using the notification cascade framework. In particular, there has often been an implicit assumption that DCT technologies will be implemented as designed by health officials, despite documented resistance to such tools in some jurisdictions.[4,25] The only other documented evidence of health official compliance comes from Switzerland, with 93.8% of cases receiving a code to upload their data,[26] substantially higher than that observed in this current study.

Strengths and limitations

The primary strength of the current study was that it was a national cohort of all COVID-19 cases. Data on token generation was available at the individual level so that we could assess any potential inequities in NZCTA uptake. It was also one of few studies that followed the notification cascade and included metrics for contact tracer uptake, adding to the validity of the findings.

The study also has a number of key limitations. First, we do not know why cases were not provided a Bluetooth token to upload their data. It is possible, although unlikely based on NZ's level of trust, that cases using the app said they were not app users when they were prompted by contact tracers. Qualitative research with public health officials may enable greater understanding of the barriers to providing cases with opportunities to upload their data. Second, we were unable to measure key steps in the notification cascade that would enable more robust evaluation of its effectiveness. For example, we do not know what proportion of contacts received a notification and importantly, what proportion of notified contacts acted on their notification. As a result, it was not possible to measure key surveillance parameters such as sensitivity and positive predictive value. However, for our evaluation of the NZCTA in the NZ context, these data limitations have had a negligible impact on our overall results, as 97.8% of the population was excluded prior to these steps.

Conclusions

The Bluetooth functionality of the NZCTA likely had a negligible impact on the pandemic response in NZ despite its exceptionally high levels of public uptake. The primary reason for the lack of impact of Bluetooth-based DCT in the NZ context was the lack of uptake from contact tracers, which exacerbated baseline inequities in access to the NZCTA. Future use of DCT technologies needs strong standard operating procedures, preferably with as few manual steps as possible, to ensure any intervention is implemented as intended and prevent driving health inequities.

A broader discussion is needed about the future role of Bluetooth contact tracing. This discussion would need to review the specific scenarios where this technology might be considered again, notably to support the control of future epidemics and pandemics, and should commence now as part of pandemic preparedness. It would also need to consider the relative benefits and costs of this technology versus alternative DCT such as QR-code contact tracing. Any future DCT solutions will need careful system design and consultation with the wider health sector and community to ensure maximal participation and effectiveness. Such systems should have quality assurance and evaluation features built into them so they can measure critical performance attributes such as sensitivity, positive predictive value, timeliness and equity.

Ethics approval

This study received a 'Minimal Risk Health Research–Audit and Audit related studies' research determination by the University of Otago Ethics Committee and approved under application HD22/080. Individual consent was not required as we were using anonymised secondary data from routinely collected information.

Implications for public health

The results highlight the need for greater consultation and collaboration with the public health sector during the development and implementation of digital contact tracing tools.

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Conflicts of interest

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References

1. Bair H, Wanger JD, Shah NR. A brief history of exposure notification during the COVID-19 pandemic in the United States, 2020—2021. *Publ Health Rep* 2022; **137**(2_suppl):23S–8S. https://doi.org/10.1177/00333549221099533.
2. Daniore P, Nittas V, Ballouz T, Menges D, Moser A, Höglinger M, et al. Performance of the Swiss digital contact-tracing app over various SARS-CoV-2 pandemic waves: repeated cross-sectional analyses. *JMIR Public Health Surveill* 2022;**8**(11):e41004. https://doi.org/10.2196/41004.

3. Menges D, Aschmann HE, Moser A, Althaus CL, von Wyl V. A data-driven simulation of the exposure notification cascade for digital contact tracing of SARS-CoV-2 in Zurich, Switzerland. *JAMA Netw Open* 2021;**4**(4):e218184-e. https://doi.org/10.1001/jamanetworkopen.2021.8184.
4. Vogt F, Haire B, Selvey L, Katelaris AL, Kaldor J. Effectiveness evaluation of digital contact tracing for COVID-19 in New South Wales, Australia. *Lancet Public Health* 2022;**7**(3):e250–8. https://doi.org/10.1016/S2468-2667(22)00010-X.
5. Rodríguez P, Graña S, Alvarez-León EE, Battaglini M, Darias FJ, Hernán MA, et al. A population-based controlled experiment assessing the epidemiological impact of digital contact tracing. *Nat Commun* 2021;**12**(1):587. https://doi.org/10.1038/s41467-020-20817-6.
6. Kendall M, Milsom L, Abeler-Dörner L, Wymant C, Ferretti L, Briers M, et al. Epidemiological changes on the Isle of Wight after the launch of the NHS Test and Trace programme: a preliminary analysis. *Lancet Digital Health* 2020;**2**(12): e658–66. https://doi.org/10.1016/S2589-7500(20)30241-7.
7. Kendall M, Tsallis D, Wymant C, Di Francia A, Balogun Y, Didelot X, et al. Epidemiological impacts of the NHS COVID-19 app in England and Wales throughout its first year. *Nat Commun* 2023;**14**(1):858. https://doi.org/10.1038/s41467-023-36495-z.
8. Wymant C, Ferretti L, Tsallis D, Charalambides M, Abeler-Dörner L, Bonsall D, et al. The epidemiological impact of the NHS COVID-19 App. *Nature* 2021;**594**: 408–12. https://doi.org/10.1038/s41586-021-03606-z.
9. Elmokashfi A, Sundnes J, Kvalbein A, Naumova V, Reinemo S-A, Florvaag PM, et al. Nationwide rollout reveals efficacy of epidemic control through digital contact tracing. *Nat Commun* 2021;**12**(1):5918. https://doi.org/10.1038/s41467-021-26144-8.
10. Mohamed Ghaith A-K, Asma Ali Al N, Sandy S, John Michael G, Jazeel A, Hamad Eid Al R. Effectiveness of Ehteraz digital contact tracing app versus conventional contact tracing in managing the outbreak of COVID-19 in the State of Qatar. *BMJ Innovations* 2022;**8**(4):255. https://doi.org/10.1136/bmjinnov-2021-000879.
11. Aronoff-Spencer E, Nebeker C, Wenzel AT, Nguyen K, Kunowski R, Zhu M, et al. Defining key performance indicators for the California COVID-19 exposure notification system (CA Notify). *Publ Health Rep* 2022;**137**(2_suppl):67S–75S. https://doi.org/10.1177/00333549221129354.
12. Rannikko J, Tamminen P, Hellsten R, Nuorti JP, Syrjänen J. Effectiveness of COVID-19 digital proximity tracing app in Finland. *Clin Microbiol Infection* 2022; **28**(6):903–4. https://doi.org/10.1016/j.cmi.2022.03.002.
13. Bannister-Tyrrell M, Chen M, Choi V, Miglietta A, Galea G. Systematic scoping review of the implementation, adoption, use, and effectiveness of digital contact tracing interventions for COVID-19 in the Western Pacific Region. *Lancet Region Health Western Pacific* 2023;**34**. https://doi.org/10.1016/j.lanwpc.2022.100647.
14. Guillon M. Digital contact-tracing in France: uptake by COVID-19 risk factor and by exposure risk. *J Public Health* 2021;**44**(3):e366–75. https://doi.org/10.1093/pubmed/fdab349.
15. Smoll NR, Walker J, Khandaker G. The barriers and enablers to downloading the COVIDSafe app – a topic modelling analysis. *Aust N Z J Publ Health* 2021;**45**(4): 344–7. https://doi.org/10.1111/1753-6405.13119.
16. Chen AT-Y, Thio KW. Exploring the drivers and barriers to uptake for digital contact tracing. *Soc Sci Humanit Open* 2021;**4**(1):100212. https://doi.org/10.1016/j.ssaho.2021.100212.
17. Jerome D, Pietrosanu M, Dhillon K. A cross-sectional population survey of physicians in Alberta, Canada about a novel provincial contact tracing smartphone app. *J Public Health* 2020;**44**(1):e141–8. https://doi.org/10.1093/pubmed/fdaa183.
18. Ferretti L, Wymant C, Kendall M, Zhao L, Nurtay A, Abeler-Dörner L, et al. Quantifying SARS-CoV-2 transmission suggests epidemic control with digital contact tracing. *Science* 2020;**368**(6491). https://doi.org/10.1126/science.abb6936.
19. Gasteiger N, Gasteiger C, Vedhara K, Broadbent E. The more the merrier! Barriers and facilitators to the general public's use of a COVID-19 contact tracing app in New Zealand. *Inf Health Soc Care* 2022;**47**(2):132–43. https://doi.org/10.1080/17538157.2021.1951274.
20. Tan ML, Senaweera O, Gunawardana A. New Zealand COVID Tracer App: understanding usage and user sentiments. In: *Proceedings of ISCRAM asia pacific conference 2022;* 2022.
21. Ali ZS, Dang H. Factors impacting the use of the NZ COVID Tracer application in New Zealand. *Smart Health* 2022:100278. https://doi.org/10.1016/j.smhl.2022.100278.
22. Tretiakov A, Hunter I. User experiences of the NZ COVID tracer app in New Zealand: thematic analysis of interviews. *JMIR mHealth uHealth* 2021;**9**(9): e26318. https://doi.org/10.2196/26318.
23. Chambers T, Anglemyer A. Pilot of a digital contact tracing card in a hospital setting in New Zealand, 2020. *J Public Health* 2022:fdac045. https://doi.org/10.1093/pubmed/fdac045.
24. Admiraal R, Millen J, Patel A, Chambers T. A case study of Bluetooth technology as a supplemental tool in contact tracing. *J Healthc Inform Res* 2022;**6**(2):208–27.
25. Chambers T, Egan R, Maclennan K, Emery T, Derrett S. Expert insights on digital contact tracing: interviews with contact tracing policy professionals in New Zealand. *Health Promot Int* 2022;**37**:1–9. https://doi.org/10.1093/heapro/daac059.
26. Ballouz T, Menges D, Aschmann HE, Jung R, Domenghino A, Fehr JS, et al. Individual-level evaluation of the exposure notification cascade in the SwissCovid digital proximity tracing app: observational study. *JMIR Public Health Surveill* 2022;**8**(5):e35653. https://doi.org/10.2196/35653.
27. Allen and Clarke. *PHU contact tracing "deep dive". Wellington (NZL): allen and clarke*. Available from: https://www.health.govt.nz/system/files/documents/publications/phu_deep_dive_rapid_report_-_synthesis_report_8_may_2020.pdf, 2020. [Accessed 13 December 2020].
28. Morgan S, Chambers T, Anglemyer A, Fyfe R, Grigg A, Teeling C, et al. *Sustaining elimination with CovidCard and enhanced digital contact tracing*. Wellington (NZL): Department of Internal Affairs; 2020. 6 June 2020. Available from: https://www.dia.govt.nz/diawebsite.nsf/Files/Proactive-releases/$file/Proactive-Release-Independent-CovidCard-Reports-FINAL.pdf. [Accessed 15 December 2020].
29. Ballouz T, Menges D, Aschmann H, Domenghino A, Fehr J, Puhan M, et al. Adherence and association of digital proximity tracing app notifications with earlier time to quarantine: results from the Zurich SARS-CoV-2 Cohort Study. *Int J Publ Health* 2021;**66**. https://doi.org/10.3389/ijph.2021.1603992.
30. Ministry of Health. *Contact tracing: lessons learnt and future model.* Wellington (NZL): Ministry of Health; 2022. Accessed via Official Information Act request.
31. Elers T, Derrett S, Emery T, Chambers T. Barely keeping the wheels on the trolley': a qualitative study of the New Zealand COVID Tracer App. *Soc Sci Med* 2024; **3562024**:117147. https://doi.org/10.1016/j.socscimed.2024.117147.
32. Zou G. A modified Poisson regression approach to prospective studies with binary data. *Am J Epidemiol* 2004;**159**(7):702–6. https://doi.org/10.1093/aje/kwh090.
33. Bendel RB, Afifi AA. Comparison of stopping rules in forward "stepwise" regression. *J Am Stat Assoc* 1977;**72**(357):46–53. https://doi.org/10.1080/01621459.1977.10479905.
34. Mickey R, Greenland S. A study of the impact of confounder-selection criteria on effect estimation. *Am J Epidemiol* 1987;**126**(4):737. https://doi.org/10.1093/oxfordjournals.aje.a115101.
35. Venables WN, Ripley BD. *Modern applied statistics with S-PLUS*. New York: Springer Science & Business Media; 2013.
36. Degeling C, Hall J, Johnson J, Abbas R, Bag S, Gilbert GL. Should digital contact tracing technologies be used to control COVID-19? Perspectives from an Australian public deliberation. *Health Care Anal* 2021:1–18. https://doi.org/10.1007/s10728-021-00441-1.
37. Grout L, Gottfreðsson M, Kvalsvig A, Baker MG, Wilson N, Summers J. Comparing COVID-19 pandemic health responses in two high-income island nations: Iceland and New Zealand. *Scand J Publ Health* 2023:14034948221149143. https://doi.org/10.1177/14034948221149143.
38. Digital Inclusion Research Group. *Digital New Zealanders: the pulse of our nation*. Wellington (NZL): Digital Inclusion Research Group; 2017. Available from: https://www.mbie.govt.nz/dmsdocument/3228-digital-new-zealanders-the-pulse-of-our-nation-pdf. [Accessed 28 August 2023].
39. Gray L, MacDonald C, Tassell-Matamua N, Stanley J, Kvalsvig A, Zhang J, et al. Wearing one for the team: views and attitudes to face covering in New Zealand/Aotearoa during COVID-19 Alert Level 4 lockdown. *J Prim Health Care* 2020;**12**(3): 199–206. https://doi.org/10.1071/HC20089.
40. Liu LS, Jia X, Zhu A, Ran GJ, Johnston D, Siegert R, et al. Measuring the missing: knowledge, risk perceptions and self-protection practices of COVID-19 among the Asian population in New Zealand: an online survey. *J Public Health* 2023: 1–18. https://doi.org/10.1007/s10389-023-01926-0.
41. Zhang W, Wu YY, Wu B. Racial/ethnic disparities in getting COVID-19 vaccine: do age, gender, and education matter? *Health Equity* 2022;**6**(1):500–7. https://doi.org/10.1089/heq.2022.0025.
42. McNulty C, Sides E, Thomas A, Kamal A, Syeda RB, Kaissi A, et al. Public views of and reactions to the COVID-19 pandemic in England: a qualitative study with diverse ethnicities. *BMJ Open* 2022;**12**(8):e061027. https://doi.org/10.1136/bmjopen-2022-061027.
43. Hearne BN, Niño MD. Understanding how race, ethnicity, and gender shape mask-wearing adherence during the COVID-19 pandemic: evidence from the COVID impact survey. *J Racial Ethnic Health Disparities* 2021:1–8. https://doi.org/10.1007/s40615-020-00941-1.
44. Bhalla A, Fang J. Leaders, institutions and people during Covid-19: secret of asian success. *J Chin Econ Bus Stud* 2022;**20**(3):253–73. https://doi.org/10.1080/14765284.2021.1989885.
45. Tang JW, Caniza MA, Dinn M, Dwyer DE, Heraud J-M, Jennings LC, et al. An exploration of the political, social, economic and cultural factors affecting how different global regions initially reacted to the COVID-19 pandemic. *Interface Focus* 2022;**12**(2):20210079. https://doi.org/10.1098/rsfs.2021.0079.
46. Waitangi Tribunal. *Hauora: report on stage one of the health services and outcomes kaupapa inquiry*. Wellington (NZL): Waitangi Tribunal; 2019. Available from: https://forms.justice.govt.nz/search/Documents/WT/wt_DOC_152801817/Hauora%20W.pdf. [Accessed 22 August 2022].
47. Harris RB, Cormack DM, Stanley J. Experience of racism and associations with unmet need and healthcare satisfaction: the 2011/12 adult New Zealand health survey. *Aust N Z J Publ Health* 2019;**43**(1):75–80. https://doi.org/10.1111/1753-6405.12835.
48. Cormack D, Harris R, Stanley J, Lacey C, Jones R, Curtis E. Ethnic bias amongst medical students in Aotearoa/New Zealand: findings from the bias and decision making in medicine (BDMM) study. *PLoS One* 2018;**13**(8):e0201168. https://doi.org/10.1371/journal.pone.0201168.

Appendix A Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.anzjph.2024.100197.