Quantifying meaningful adoption of a SARS-CoV-2 exposure notification app on the campus of the University of Arizona

Joanna Masel[1], Alexandra Shilen[2], Bruce Helming[3], Jenna Rutschman[4], Gary Windham[5], Kristen Pogreba-Brown[2], Kacey Ernst[2]

1. Department of Ecology & Evolutionary Biology, University of Arizona, Tucson, AZ, USA

2. Mel and Enid Zuckerman College of Public Health, University of Arizona, Tucson, AZ, USA

3. Campus Health, University of Arizona, Tucson, AZ, USA

4. College of Science, University of Arizona, Tucson, AZ, USA

5. Information Technology, University of Arizona, Tucson, AZ, USA

Abstract

Objective. To measure meaningful, local exposure notification adoption without in-app analytics.

Methods. We surveyed app usage via case investigation interviews at the University of Arizona, with a focus on the period from September 9 to November 28, 2020, after automating the issuance of secure codes to verify positive diagnoses within the test result delivery system. As independent validation, we compared the number of secure codes issued to the number of local cases.

Results. Of cases interviewed by university case investigators, 46% (286/628) reported having the app, and 55% (157/286) of these app users shared their positive SARS-CoV-2 test result in the app prior to the case investigation interview, comprising 25% (157/628) of all interviewed cases. This is corroborated by a 33% (565/1,713) ratio of code issuance (inflated by some unclaimed codes) to cases. Combining the 25% probability that a primary case rapidly shares their diagnosis with a 46% probability that the secondary case can receive exposure notifications, an estimated 11% of transmission pairs exhibit meaningful app usage. We attribute these high rates, despite the lack of "push" notifications, to a successful marketing campaign that identified social influencers.

Conclusions. Usage can be assessed in clusters, without in-app analytics. With marketing, high uptake in dense social networks like universities make exposure notification a useful complement to traditional contact tracing. Integrating verification code delivery into patient results portals was successful in making the exposure notification process rapid.

Introduction

Smartphone applications (apps) for exposure notification have the potential, given sufficient uptake, to significantly reduce the spread of SARS-CoV-2 (1). They do so not by replacing contact tracing, but by making contact notification faster, more scalable, and potentially more acceptable due to greater privacy (1). The University of Arizona community piloted the Covid Watch app, which through the Google/Apple Exposure Notification API (GAEN), uses Bluetooth to measure date, distance, and duration of contact, and assess infection risk (2). App users who tested positive for SARS-CoV-2 could anonymously trigger notifications, including testing and quarantine recommendations, for other Covid Watch users with whom they had been in close contact while infectious.

The focus of this study is to quantify meaningful app uptake. App download numbers are readily accessible, but overstate active app usage (3). Effective uptake requires not just app installation in both a primary and a secondary case, but also that the primary case report a positive SARS-CoV-2 test result by obtaining and entering a secure verification code (either from their results portal or medical provider). The potential for exposure notification to prevent SARS-CoV-2 transmission depends not on overall usage in a community, but on usage specifically among individuals who go on to be infected. One concern is that individuals who are more likely to download an exposure notification app are generally more compliant with public health guidelines, and so may be less likely to be infected by SARS-CoV-2, making population statistics overestimates of effective usage. With the help of a third party, the University of Arizona used social marketing tools to promote app usage, with a focus on reaching students via identified influencers (4, 5); here we assess the outcome.

Methods

Evaluating GAEN apps is challenging because of their strict privacy protections (6). We therefore incorporated two questions into case investigation interviews: (i) Have you downloaded the Covid Watch app?; (ii) If yes, did you already enter the verification code following your positive test? A portion of the faculty, staff, and students who tested positive through the on-campus testing program were assigned to a university contact tracing team (SAFER) by the county health department (7) (the remainder were interviewed by county investigators and fall outside the scope of the current study). Assignment of cases to the University of Arizona SAFER team varied over the time period covered in this report due to changing patterns of incidence. Cases who lived on-campus (dorms and Greek housing) were consistently assigned to SAFER throughout this time period. For off-campus cases tested through the University of Arizona testing program, a surge in cases associated with campus necessitated additional support from county investigators, so from September 10 to October 30, county health department staff investigated all off-campus cases. Starting October 31 and continuing on, SAFER investigated all cases tested through the University of Arizona testing program and anyone who provided an ‘on-campus’ address, even if they were tested off-site. The team filtered the case data through code developed in R by known on-campus addresses each day to create these investigation assignments.

Upon first launch on August 23, verification codes were given over the phone by Campus Health. Beginning September 9, end users, when viewing their positive test result in the “Test All Test Smart” portal that supports the university’s high-volume diagnostic testing, were prompted to retrieve a code automatically if they had the Covid Watch app. Some individuals tested positive twice, e.g. once by antigen test and once by PCR. Positive test results, combined across both Campus Health and the Test All Test Smart program, were de-duplicated to calculate number of cases, by discounting subsequent positive test results for the same individual if they occurred within a 90 day window from the first positive test.

We calculate the fraction of positive tests that lead to a request for a verification code by dividing number of codes issued by number of cases. We count verification codes at point of issue rather than upon usage, but because obtaining a code requires action from an infected individual (either a phone call or clicking on a request link), we expect this to be only a slight overestimate.

Our data span August 23 to November 28 (Fall semester), during which there was a significant outbreak of SARS-CoV-2 in the student population. Verification code issuance peaked in the same week as confirmed cases (Figure 1). To evaluate the impact of automated code delivery, we compare data before versus after September 9.

Use of aggregate data collected under public health surveillance guidelines was deemed not human subjects research by University of Arizona privacy officers in consultation with the university's IRB.

Results

Campus testing programs recorded 2,728 positive tests from August 23 to November 28, representing 2,360 cases. Of these cases, the University of Arizona team was assigned 1,359 cases to investigate and conduct contact tracing, while the remaining cases were investigated by the local health department and are not included in our sample. The university contact tracing team succeeded in reaching and interviewing 64% (876/1359) of their assigned cases, in all cases including the survey questions. Among these interviewed cases, 35% (302/876) reported no contacts to case investigators. Results are summarized in Table 1.

The proportion of interviewed cases who had downloaded the app improved during the initial weeks of the launch, rising from 38% (95/248) before September 9 to 46% (286/628) over the remainder of our reporting period. More strikingly, the proportion of app-using cases that had entered a positive diagnosis code into their app prior to the case interview, enabling rapid contact notification, rose from 32/95 (34%) before September 9 to 157/286 (55%) after. This latter comparison shows how the introduction of automated code distribution improved usage.

From September 9 onward, 25% (157/628) of the interviewed cases both had the app and had entered a positive diagnosis code. However, interviewed cases may generally be more compliant with public health guidelines than other cases, and thus have higher app use. It is therefore reassuring that we get a similarly high estimate of 33% for this date range by dividing the 565 verification codes issued by the 1,713 cases testing positive at our campus testing facilities (rising from 48/647 (7%) prior to September 9 when codes were issued only by phone).

Because cases were asked whether they had entered verification codes prior to case investigation interviews, our results demonstrate that notification via the Covid Watch app was more rapid not only than traditional contact tracing at the University of Arizona, but also than digital exposure notification workflows used elsewhere in which case investigators provide verification codes over the phone. Our automated code delivery via an end-user test results portal is now adopted by commercial test providers in Arizona.

Public Health Implications

We propose and estimate a metric of meaningful usage among cases. Because the app's purpose is to quarantine the infected prior to diagnosis, focusing on cases is more epidemiologically meaningful than usage among the general population. We consider the scenario where a primary case infects a secondary case within a tightly interconnected college campus, and estimate the probability that both cases have used the app to the minimum necessary level to potentially impact transmission. From September 9 onward, the estimated probability of sufficient usage by the primary case is 25% (where verification code entry is required, occurring at a similar 55% rate as Germany (8)) and 46% for the secondary case (requiring only app activation). Combining these by assuming a well-mixed population, and neglecting transmission from outside campus given low community prevalence at the time this pilot study was conducted, app usage is estimated to affect 11% of transmission pairs (Table 1). In a structured population where individuals in the same transmission pair have more similar app usage rates, this value will be higher than 11%.

Our app usage metric can be used to estimate the expected reduction in R(t) due to the direct impact of exposure notification influencing the quarantine, testing and ultimately isolation behavior of secondary cases. This reduction could be ~11% if 1) all cases carried their phones with them at the time transmission occurred, 2) primary cases are tested rapidly, 3) the app detects exposures that led to transmission, and 4) notifications following infection eliminated forward disease transmission by sufficiently changing the behavior of secondary cases. The direct reduction in R(t) will be smaller, because of violations in these assumptions, especially the fourth given reports of low quarantine compliance (9, 10). However, R(t) is also indirectly reduced when the far larger number of exposure events that do not lead to transmission also lead to behavior change, which either prevents infection in the notification recipient, or elicits first quarantine and then isolation after they have been infected by a different exposure within the same social network (11).

To promote end-user adoption, most U.S. States have relied on "push" notifications sent out by Apple and Google directly to smartphone users' phones. These were not available at the time of this study, and are currently available only for Apple's own Exposure Notification Express system and not for custom iOS apps (12). Another strategy to promote adoption is to use the same app to check in to venues as a privacy-preserving alternative to giving personal details (1); this is unavailable in jurisdictions that do not collect venue attendance for possible contact tracing purposes. Here we have shown that it is possible to achieve high adoption within a tightly interconnected community using a social influencer marketing strategy, without the advantage of push notifications or a multi-purpose app.

Here we have proposed a new metric for assessing app usage within a tightly interconnected community that does its own testing and tracing. Usage on the University of Arizona campus is high enough to make it a useful tool that complements and augments traditional contact tracing. Highly interconnected communities such as college campuses, large workplaces, tribal nations, and congregate living settings could benefit from targeted adoption campaigns. Further evaluation is needed to assess the extent of compliance with quarantine among contacts receiving notification via such apps, which is a key determinant of the overall impact of EN on reducing SARS COV-2 transmission.

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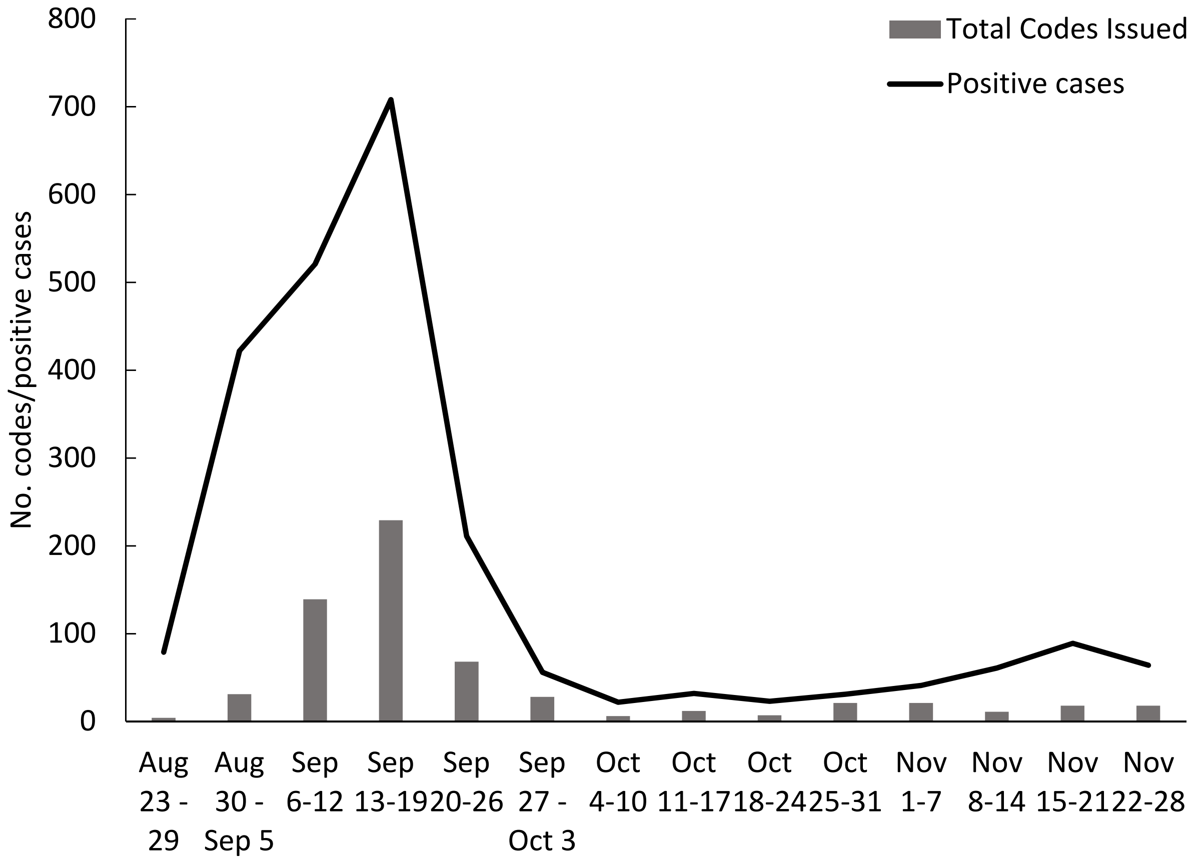

Figure 1. The number of verification codes issued tracks the number of cases during an outbreak among students on the campus of the University of Arizona. The total number of codes issued represented only 7% of the number of cases prior to the automation of code delivery on September 9, and rose to 33% for the remainder of the study period.

Metric	Aug 23 - Sep 8	Sep 9 - Nov 28	Total
Positive Codes issued by phone	48	166	214
Positive Codes issued via test results portal	0	399	399
Total Positive Codes issued	48	565	613
Positive tests	676	2052	2728
Cases	647	1,713	2,360
Cases investigated by university contact tracing team			1,359
Number of cases reached by university contact tracing team	248	628	876
Downloaded the app	95	286	381
Entered a code to share their positive test	32	157	189
Downloads/Cases Reached	38.3%	**45.5%**	43.5%
Code Entries/Cases Reached	12.9%	**25.0%**	21.6%
Codes Issued/Cases	7.4%	**33.0%**	26.0%
R(t) Adoption metric (primary case and secondary case, product of Downloads/Cases and Code Entries/Cases)	4.9%	**11.4%**	9.4%

Table 1. The frequency with which cases used the Covid Watch app increased far more following the automation of verification code delivery than did the frequency with which cases had the app downloaded at the time of case interview. Key numbers following code delivery automation are shown in bold.