Project Report
ACTA-2

# Bluetooth Low Energy (BLE) Data Collection for COVID-19 Exposure Notification

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13 April 2022

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# ABSTRACT

Privacy-preserving contact tracing mobile applications, such as those that use the Google-Apple Exposure Notification (GAEN) service, have the potential to limit the spread of COVID-19 in communities; however, the privacy-preserving aspects of the protocol make it difficult to assess the performance of the Bluetooth proximity detector in real-world populations. The GAEN service configuration of weights and thresholds enables hundreds of thousands of potential configurations, and it is not well known how the detector performance of candidate GAEN configurations maps to the actual "too close for too long" standard used by public health contact tracing staff. To address this gap, we exercised a GAEN app on Android phones at a range of distances, orientations, and placement configurations (e.g., shirt pocket, bag, in hand), using RF-analogous robotic substitutes for human participants. We recorded exposure data from the app and from the lower-level Android service, along with the phones' actual distances and durations of exposure. Data from this collection have been shared with the Exposure Notification community of research and practice, and have been incorporated into EN-related models and public health EN deployment decisions.

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# 1. BACKGROUND

Automated digital contact tracing was proposed early in 2020 as a practical way to augment the efforts of traditional contact tracing teams and slow the spread of the SARS-CoV-2 virus. The PACT, or Private Automated Contact Tracing, protocol used cryptographic protection measures to enable two devices such as smartphones to communicate securely and privately when nearby, and to share information about a COVID-positive test with public health and with those who were nearby during the infectious window, without divulging the identity of the infected person [1].

In May 2020, the first version of the Google Apple Exposure Notification (GAEN, or EN) service was released [2]. Exposure Notification was designed to help an individual become aware of recent "close contact" events they may have experienced, by listening for specialized Bluetooth messages and using the signal strength of those messages to estimate the duration and proximity of the encounters. The GAEN risk scoring algorithm uses a scheme of weights and thresholds to assign an exposure risk value to each exposure, and sums the score of each exposure to arrive at a daily cumulative score. If the total score exceeds a specified threshold, the user of the EN service sees an alert on their smartphone, advising them of the risky exposure and recommending next steps (e.g. testing and self-quarantine), alongside contact information for the local public health authority [3].

The selection of appropriate weights and thresholds for EN is a key determinant of the sensitivity (percentage of correct detections of risky encounters) and specificity (avoidance of incorrect detections) of the Bluetooth-based proximity detector, when a given standard is defined. The U.S. Centers for Disease Control and Prevention (CDC) had set the definition of a "close contact" for contact tracing activities as "15 or more minutes at six or fewer feet" [4]. However, Bluetooth is not terribly accurate at estimating distance between a pair of devices, so some "fuzziness" in the estimate was deemed tolerable in order to make use of the ubiquity of Bluetooth-equipped smartphones. Tuning the risk scoring configuration to achieve a desired level of sensitivity, while understanding the tradeoff in specificity, was an early and recurring concern of public health teams who wished to use EN in their communities.

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## 2. RELATED WORK

Quantifying the performance of the Bluetooth detector required data. In May 2020, MIT Lincoln Laboratory performed preliminary measurements for a DARPA-funded PACT effort, during strict lockdown conditions, in staff members' homes. In these tests, staff and family members exercised the Bluetooth radios with a custom app, as EN was not yet available. The app collected signal strength measurements with iPhones in a variety of placements (in pockets, in bags, in hands) and at varying rotations away from line-of-sight orientations. The dataset was published on GitHub with other PACT-related datasets [5], and confirmed initial hypotheses that phone placement and orientation could have a significant effect on the perceived signal strength of the Bluetooth messages [6].

Apple and Google were aware that hardware diversity and power budget considerations would result in unequal transmission power selections for different smartphone devices. Therefore, when they released the first version of the EN service, it included a calibration offset value and a transmit power value for each model of phone. For some models, the values were derived from a single-orientation measurement campaign; others were extrapolated based on hardware similarity [7]. More extensive follow-on calibration campaigns were conducted by phone vendors, and the calibration values were updated on users' phones through updates to the EN service throughout 2020, although many models of Android phones still are listed with the lowest level of "calibration confidence" in early 2022.

Due to the well-documented variations in perceived attenuation, early adopters of the EN service sought early measurement and analysis of how the implemented system might be performing, and how well it matched the sensitivity and specificity needs of public health. Early experiments in Europe included a data collection performed with volunteers on public transit buses [8] and in a large office building [9].

Taking end-to-end measurements of whether EN alerts are triggered in close proximity/over long durations, or not triggered outside of close proximity/over short durations, provides a very limited assessment capability. It requires a specific set of weights and thresholds to be preselected and programmed into the EN application, and only provides information about the performance of that specific configuration. That might still have been adequate to assess the performance of EN for a handful of test configurations, but two factors compelled us to focus less on the weights and thresholds, and more on collecting as much low level BLE message data as possible:

1. The first version of the GAEN risk scoring algorithm [10] permitted an astronomical number of arithmetically valid configurations, and even a coarse-grained reduction to "sensible" configurations suggested at least 12,500 candidate configurations.

2. Google and Apple announced in July 2020 that the original risk scoring algorithm was being replaced with a new version ("ExposureWindow" mode), and although the original scoring was

still available, public health partners were strongly encouraged to move to the new risk scoring and configuration model [11].

The new scheme for configuring EN still relied on a simplified “bucketing” of attenuation measurements and duration, which produced an estimate of weighted “minutes at attenuation”. However, the new scheme was different enough that exposures assessed under the old risk scoring algorithm would not necessarily result in the same number of notifications as if they were assessed under the new algorithm.

For these reasons, MIT LL was tasked with conducting a new data collection campaign using the CDC’s “Guardian” reference application, and recording the individual RSSI measurements, so that the same exposure events could be re-processed with different configurations, even if the risk scoring algorithm were to be updated again. Additionally, the testing would be conducted onsite at the Autonomous System Development Facility, rather than in homes, and mannequins would be used in place of human participants, both to protect staff from possibly infecting each other and to eliminate individual body variation as one of the test variables. Finally, the tests would include longer indoor distances than were obtainable in homes and apartments.

# 3. EXPERIMENTAL DESIGN

Our objective was to collect a high-quality dataset of actual EN messages, transmitted by the then-current implementation of the EN Service, under more representative usage (i.e., not tabletop or anechoic chamber measurements), and using well-defined and reproducible physical configurations. We aimed to control for phone distance, placement or “carriage”, orientation, and body absorption, and hardware variation, and EN “calibration confidence”. To do this, we selected a single model of Android phones listed as having the highest of three calibration confidence levels. We were able to obtain a developer credential from Google that made low-level debugging information about Exposure Notification messages available for inspection and exfiltration. Because Apple did not provide developer entitlements that would allow us to record individual EN message signal strengths, this type of data was not available to us from iPhones.

The CDC’s Informatics Innovation Unit had developed a basic EN app from the Google-provided reference implementation, and granted us access to both the source code of their “Guardian” app and a prototype key server so that we could confirm our test setup was working correctly.[1] Our software testbed, shown in Figure 1, included an adapted prototype EN app, the CDC-hosted prototype key and verification servers, and a Java program wrapper of the open source risk scoring algorithm, which enabled us to re-run the algorithm on the collected data to better understand idiosyncrasies and the effects of different EN configurations. Due to the privacy-preserving design of EN, and the implementation decisions made by Google, it was necessary for us to perform a key exchange and matching attempt in order to decrypt, record, and validate the logged Bluetooth information. Although the implementation required us to select configuration weights and thresholds, we were concerned only with recording the RSSI signal strength and timestamps of the received messages, as these could be used to “replay” an exposure mathematically with any configuration, and predict whether a notification would be triggered. Likewise, we kept the infectiousness stored in the diagnosis key’s metadata constant in all tests.

[1] In fact, our pre-test validation phase revealed a bug in the Guardian app’s risk scoring implementation.

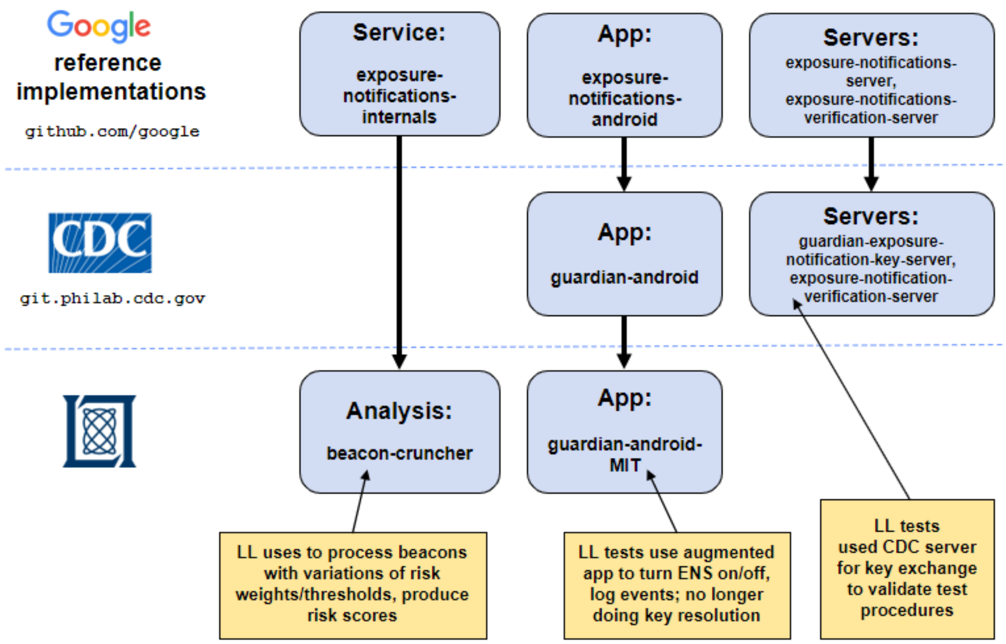


*Figure 1: Software test infrastructure "family tree" of related code.*

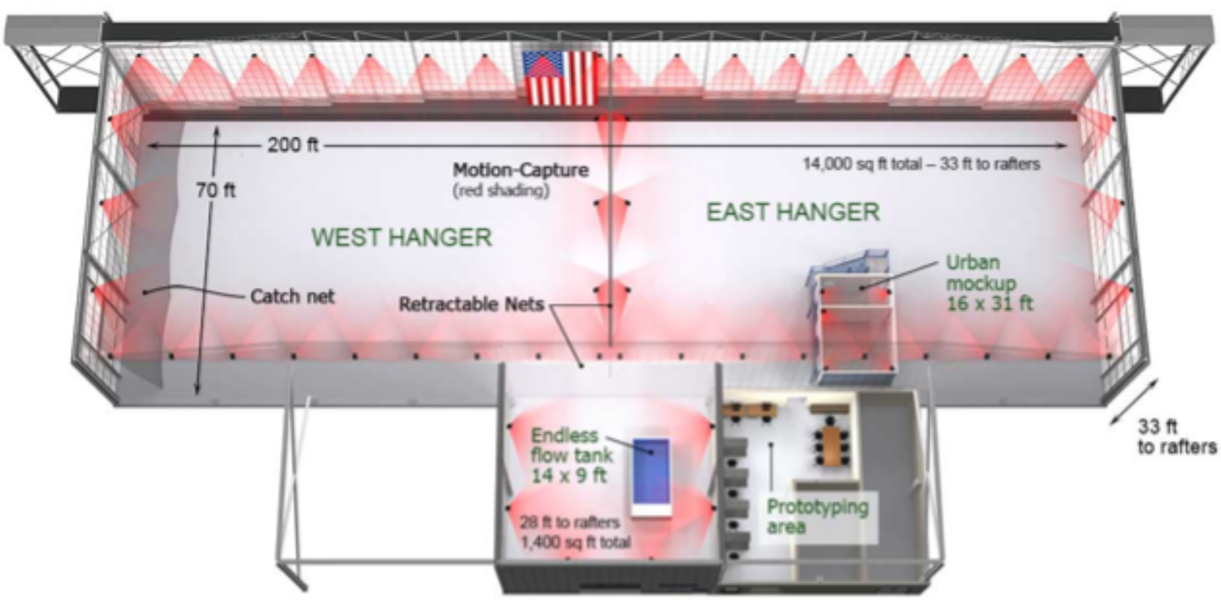


*Figure 2. Autonomous Systems Development Facility (ASDF) floor plan.*

Our test environment was the East Hangar section of the Autonomous Systems Development Facility, which enjoys a 400,000 ft3 space augmented with a real-time motion capture system (Figure 2) [12]. The robotic mannequins used for testing had been coated in a foam skin that approximated radio frequency (RF) absorption similar to that of an adult human, as measured in the MIT LL anechoic chamber earlier in the pandemic. The mannequins were mounted on robotic platforms and augmented with motion-capture targets on their heads, as well as on the phones' carriage locations. The motion capture system recorded the position and orientation of each "person" and phone during testing.

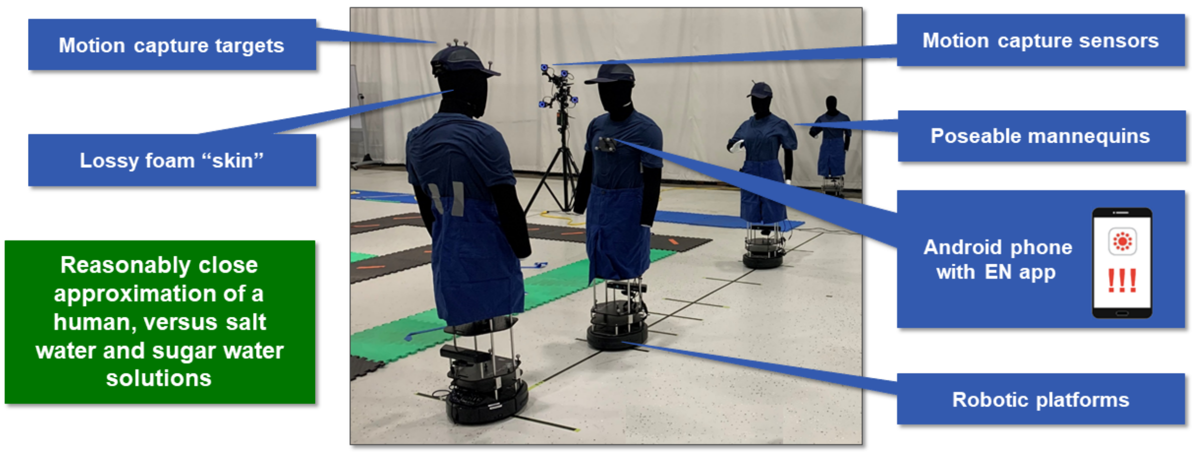


*Figure 3: Data collection hardware, software, and infrastructure in the ASDF.*

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Figure 4 shows how the mannequins were used to collect data at preplanned distances and orientations. The phones were placed in the front shirt pocket, the front pants pocket, or a bag worn by the mannequin. Test durations ranged from 5-25 minutes and distances ranged from 0.5-60.0 feet. The mannequin and phone orientations were selected for zero-body-blocking, one-body-blocking, and two-body-blocking tests, as shown in Figure 4.

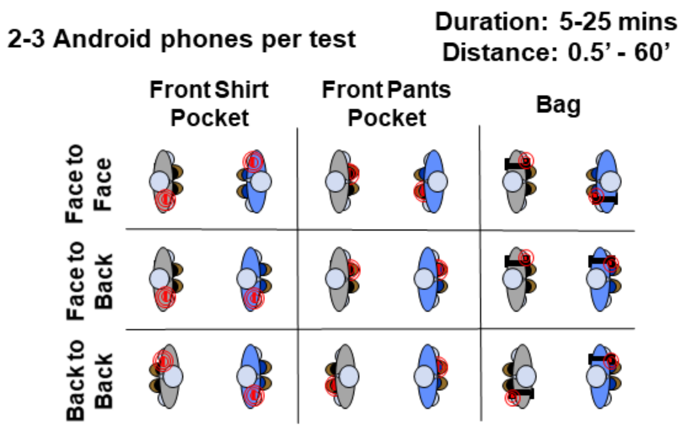


*Figure 4: Physical configurations used in testing.*

In order to create statistically relevant data, it was important to maximize the number of tests performed with unique combinations of physical configurations. The testing scenarios laid out 92 individual tests with 2 or 3 phones/mannequins per test. This enabled the team to generate 196 individual results and compile them into a database for analysis.

**TABLE 1:**

**Summary of Physical Configurations Under Test**

| | | Number of phones | Number of Tests | Carriage | Test Duration |
|---|---|---|---|---|---|
| Scenario | Large Room | 3 | 12 | Shirt Pockets, Pants Pockets, Bags | 15 min |
| | Large Room | 2 | 40 | | 5-25 min |
| | Small Room | 2 | 40 | | 15 min |
| Totals | | 196 unique samples | 92 | | ~1380 min |

# 4. DATA COLLECTION PROCEDURE

Prior to each exposure trial, the phones' records of previous exposures were erased from the Exposure Notification service and from the app. Each phone was placed in position in a mannequin's hand, pocket, or bag. The beginning of each exposure period was recorded from the phones' system clocks. During the exposure period, the mannequins moved through the test space as scripted for each distance and duration under test. The overall amount of motion was roughly intended to correspond to reality; because the EN sampling rate is on the order of 2–5 minutes, however, it was not necessary to have the phones in near-constant motion.

At the end of each exposure period, we deactivated EN on each phone in the same order in which it was activated. We then shared the Temporary Exposure Key from the sick phone with each of the exposed phones, and recorded whether the phone showed an alert to the user. We saved a copy of the Android system logs, which recorded the low-level timestamps and signal strength measurements of the beacons heard by each phone, and the confirmation of the key matching procedure. These data files, in combination with our ground truth positional and time data, were processed after the test. The specific system logs we used were the "bugreport" files with "dumpsys" records for each EN message. We extracted the system clock timestamps, raw RSSI values, Rolling Proximity Identifiers (RPIs), encrypted metadata, version information, and previous scan times from the EN log lines and dumpsys records, matching the encrypted and unencrypted metadata to ensure that no "stray" messages were recorded from bystander phones. The motion capture system clock was used as a test time reference, and the videos of test runs were examined against the log files to determine whether the phone timestamps should be offset to correlate to recorded distances at which RSSI samples were recorded. If RSSI was sampled while the mannequin was in motion, the samples were discarded.

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# 5. RESULTS

At the time of our data collection exercise, little was known about the performance of EN “in the wild”. The experiments attracted interest from our colleagues at Google, Apple, and the NHS COVID-19 app implementors. The sponsor permitted us to share our data with these researchers, which enriched technical meetings and facilitated the analysis of combined EN data for both Androids and iPhones. The collected data have been publicly released to GitHub [13].

We examined the effect of absorption and carriage state on the perceived signal strength at the receiving phone, i.e., the phone of a potential “close contact” of someone with COVID-19. Figure 5 shows the relationship between ground truth distance, and recorded signal strength, or attenuation, and compares the effects of absorption by bodies, and phones placement. When no bodies were in the way, attenuation did correlate fairly well with distance, although there was still noticeable variance over 5’ increments. The position of the phone on the mannequin had a smaller effect than the signal loss from body-blocking, and at distances greater than 10–12 feet, the difference in attenuation is negligible for one versus two bodies.

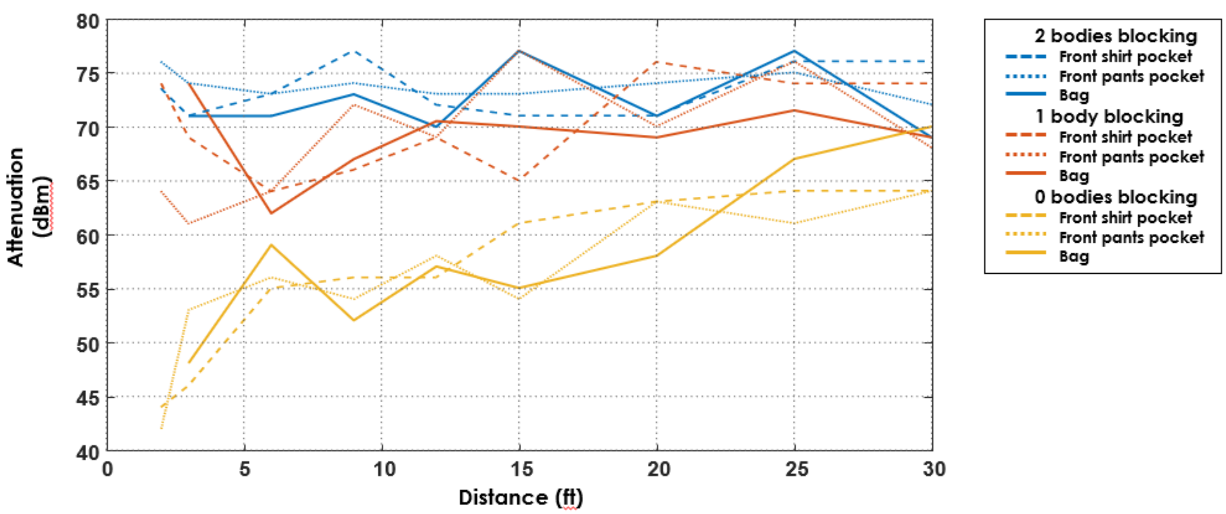


*Figure 5: Attenuation vs actual distance in large indoor space.*

The data confirm that Bluetooth signal strength, even when calibrated according to the EN specification, is still going to be a noisy estimate of distance. If extra information regarding the local environment of the phone (e.g., is it in a bag or pocket) and of the individual (e.g., are they indoors or outdoors) could be made available to the risk calculation, the attenuation component of the risk score could be tuned to contribute more appropriately to the total risk score.

However, to put this finding in perspective, recall that the attenuation measurement ultimately is used to estimate not distance, but infection risk. As scientific understanding of COVID-19 transmission has increased, it has become more apparent that risky exposures cannot be characterized by a "bright line" threshold for either distance or duration. The imprecision inherent in the distance and duration estimates may actually prove to be an appropriate match to the inexact risk of transmission in the real world (due to compounded variations in aerosol distribution, personal susceptibility, and other factors).

The data from these experiments have been used to inform the development and refinement of the Bluetooth Low Energy Model of User Risk (BLEMUR) [14], and indirectly contributed to sensitivity and specificity parameter selection for the Simulated Automated Exposure Notification (SimAEN) model and web-based tool for public health [15], [16], [17]. Analysis outputs from this dataset have been presented to public health teams through CDC-hosted community of practice calls, direct technical exchanges with state departments of public health, and two Risk Scoring Symposia hosted by the Linux Foundation Public Health [18], [19].

# 6. CONCLUSION

In order to fully assess the design and performance of a distributed sensor network such as GAEN, it is necessary to examine performance at multiple levels, from the system as a whole down to the individual sensor performance under well-understood conditions. Our data collection efforts in 2020 helped to close the gap between simple benchtop and anechoic measurements for two-phone interactions, and “black box” or “in the wild” performance assessments which lack ground truth information about timing, proximity, and environmental effects. The data were rigorously inspected and validated, timestamped, and correlated to ground truth data for distance, orientation, and duration. The test procedure we developed for this exercise laid the foundation for a more extensive data collection in early 2021, and contributed directly to parallel modeling efforts and the decision processes of public health teams as they piloted and launched Exposure Notification systems in their regions.

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# GLOSSARY

| | |
|---|---|
| ASDF | Autonomous Systems Development Facility |
| Attenuation | Reduction of signal amplitude |
| BLEMUR | Bluetooth Low Energy Model of User Risk |
| CDC | Centers for Disease Control and Prevention (United States) |
| COVID-19 | Coronavirus disease caused by the SARS-CoV-2 virus |
| DARPA | Defense Advanced Research Projects Agency |
| EN | Exposure Notification |
| GAEN | Google-Apple Exposure Notification |
| MIT LL | Massachusetts Institute of Technology Lincoln Laboratory |
| NHS | National Health Service (United Kingdom) |
| PACT | Private Automated Contact Tracing |
| RF | Radio frequency |
| RPI | Rolling Proximity Identifier, a short-lived token generated from the TEK |
| RSSI | Received signal strength indicator |
| SARS-CoV-2 | Severe acute respiratory syndrome coronavirus 2 |
| SimAEN | Simulated Automated Exposure Notification |
| TEK | Temporary Exposure Key, a cryptographic token generated on the smartphone once per day |

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**13. SUPPLEMENTARY NOTES**

**14. ABSTRACT**

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