Vetting Security and Privacy of Global COVID-19 Contact Tracing Applications

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ABSTRACT
The rapid spread of COVID-19 has made traditional manual contact tracing to identify potential persons in close physical proximity to an infected person challenging. Hence, a number of public health authorities have experimented with automated contact tracing apps. While the global deployment of contact tracing apps aims to protect the health of citizens, these apps have raised security and privacy concerns. In this paper, we assess the security and privacy of 34 exemplar contact tracing apps using three methodologies: (i) evaluate the design paradigms and the privacy protections provided; (ii) static analysis to discover potential vulnerabilities and data flows to identify potential leaks of private data; and (iii) evaluate the robustness of privacy protection approaches. Based on the results, we propose a venue-access-based contact tracing solution, VenueTrace, which preserves user privacy while enabling proximity contact tracing. We hope that our systematic assessment results and concrete recommendations can contribute to the development and deployment of applications against COVID-19 and help governments and application development industry build secure and privacy-preserving contact tracing applications.

1 INTRODUCTION
COVID-19 is now a global pandemic affecting over 200 countries, after its first recorded outbreak in China in December 2019. To counter its spread, numerous measures have been undertaken by public health authorities, e.g. quarantining of people, lock-downs, curfews, physical distancing, and mandatory use of face masks.

Identifying those who have been in close contact with infected individuals, followed by self-isolation (so called contact tracing) has proven particularly effective [47]. Consequently, contact tracing has emerged as a key tool to mitigate the spread. However, manual contact tracing, using an army of "detectives" is not trivial and has proven challenging for many countries, e.g. UK and Italy. Notably, it is difficult due to the rapid and exponential growth patterns of the virus and the increased demands on qualified human resources. After 5 months of the pandemic, the number of daily new cases has increased more than 80 fold. Thus, in many countries it has become extremely difficult to perform manual contact tracing [19, 24, 36].

Government authorities around the world, together with industry, have sought to address the challenge by developing contact tracing applications and services. A plethora of apps and services are currently deployed around the globe. These include the Health Code in China [49], the public COVID-19 website in South Korea [14], and the mobile contact tracing apps released in Singapore [32], Israel [44], and Australia [22, 23]. Contact tracing apps operate by recording prolonged and close proximity interactions between individuals by using proximity sensing methods, e.g. Bluetooth. The data gathered allows notifications to be generated to inform persons of a potential exposure to the virus.

Proponents argue that the low cost and scalable nature of contact tracing apps make them an attractive option for health authorities. Despite this, contact tracing apps are not universally popular, with a number of prominent critics. They have proven particularly controversial due to potential violations of privacy [37], and security consequences from the mass-scale installation of (rapidly developed) apps across entire populations. Despite attempts to alleviate these concerns by both governments and industry, it is well known that the anonymization of individual information is a challenging problem [21]. This study, to the best of our knowledge, performs the first security and privacy vetting of contact tracing apps. We describe our key contributions below:

- We assess the security and privacy of 34 worldwide Android contact tracing applications, listed in Table 3. We discover about 70% of the apps pose potential security risks due to: (i) employing cryptographic algorithms that are insecure or not part of best practice; and (ii) storing sensitive information in clear text that could be potentially read by attackers. Over 60% of apps pose vulnerabilities through Manifest permissions, e.g. allowing permissions for backup (hence, the copying of potentially unencrypted application data). Further, we identify that approximately 75% of the apps contain at least one tracker, potentially causing serious privacy leakage, i.e. data leaks that lead to exposing private information, to third parties. To facilitate further research, we will publicly release the dataset, the scripts developed for analysis, and security assessment reports in due course.
- We analyze user privacy exposure and privacy protections provided by 10 solutions—covering 3 different frameworks (PACT [18], Covid Watch [54], and PEPP-PT [57]), the Coronavirus Disease-19 website [14], and 6 applications—from 7 countries around the world. We establish a threat model and analyze the vulnerabilities of the apps to multiple privacy attacks. The results demonstrate that there is no solution that is able to protect users’ privacy against all of attacks investigated. The replay attack, in which a malicious user
We believe our study can provide useful insights for governments, worldwide. Given the large number of contact tracing apps and proposed solutions for containing infectious diseases now and in the future.

A range of contract tracing applications (or “apps”) are used worldwide; and we envisage three groups of contact tracing systems. Our VenueTrace proposal has the capability to significantly increase the privacy protections for citizens whilst being securely implemented.

We have disclosed our findings and detailed security and privacy risk reports to the related stakeholders on 23 May 2020, at 11 am, UTC. We have received acknowledgements from numerous vendors, such as MySejahtera (Malaysia), Pakistan’s National Action Plan for COVID-19 (Pakistan), Contact Tracer (USA), and Private Kit (USA). We believe our study can provide useful insights for governments, developers and researchers in the software industry to develop secure and privacy-preserving contact tracing apps. We hope the results and the proposed contact tracing approach will contribute to increasing the trustworthiness of solutions to contain infectious diseases now and in the future.

2 CONTACT TRACING APPLICATIONS

A range of contact tracing applications (or “apps”) are used worldwide. Given the large number of contact tracing apps and proposed solution frameworks, we survey a representative sample to more broadly study the architectures employed, design paradigms and the privacy exposure of the user groups we identified in Section 2.1.

2.1 Users Groups and Privacy Exposure

We define model user groups and privacy exposure levels to aid our investigations into app architectures (in Section 2.2) and privacy vetting (in Section 4). We envisage three groups of contact tracing app users, based on their health status. We describe the three user groups below and analyze their privacy exposure in Section 2.2.

- **Generic user.** A typical user of the contact tracing system, who is healthy or has not been diagnosed yet.
- **At-risk user.** Alice, who has recently been in contact with an infected user, Bob. Ideally, Alice will receive an at-risk alarm from her application.
- **Diagnosed user.** As a diagnosed patient, Bob will be asked to reveal his private information as well as the information of at-risk users to the health authorities, e.g. the diagnosis of his infection, his movement history, the persons he has been in contact with.

We define user group exposures in different apps using five levels:

- **Level I:** "No data is shared with a server or users”, the most secure level in which there is no user data shared.
- **Level II:** “Tokens are shared with proximity users”, a medium exposure level with only tokens containing no Personal Identifiable Information (PII) exchanged between users.
- **Level III:** “Tokens are shared with the server”, a medium exposure level with tokens exposed to the server.
- **Level IV:** “PII is shared with a server”, a high risk exposure level in which the users’ PII is shared with the server.
- **Level V:** “PII is published to public”, the highest risk exposure level.

2.2 Analysis of Design Paradigms and User Privacy Exposure

We select 10 well known contact tracing solutions—including both current apps and proposed frameworks. Table 1 presents an overview of the 10 selected solutions. Four of the selected solutions are developments of apps used from the early stages of the pandemic (supported by governments such as China, South Korea, Singapore, and Israel). The one service and a proposed framework from Europe were selected because they are the first solutions that enable anonymous identifier exchange. We have also selected three solutions that are about to or have already been deployed from North America and one app deployment from Oceania. As summarized in Table 2, all 10 solutions have user privacy exposure to some extent. We next discuss them in the context of the two broad categories of: (i) centralized architectures; and (ii) decentralized/distributed architectures.

**Centralized solutions.** Many solutions utilize a centralized system in which the central server is responsible for: (i) collecting the contact records from diagnosed users; and (ii) health status evaluation for users and at-risk user determination. In some East Asian countries, e.g. China and South Korea, where the outbreaks first occurred, contact tracing systems were quickly developed and released. The systems helped health authorities to successfully control the spread of COVID-19, but a huge amount of Personal Identifiable Information (PII) was collected.

In South Korea, the Coronavirus Disease-19 website [14] (#7 in Table 1) is supported by the Ministry of Health and Welfare. Although Alice’s privacy is protected as no data is required from her, the system publishes Bob’s information to the public (marked as Level V in Table 2). The information exposed includes gender, nationality, age, diagnosis date, hospital, and movement history (removed in the latest version). This directly puts Bob at risk of being re-identified, raising serious privacy concerns. For example, as reported by The Washington Post [35], in Cheonan, a city in South Korea, a text alert to residents showed that an infected person visited “Imperial Foot Massage at 13:46 on 24 February”.

In China, QR-code contact tracing apps were developed by the two Tech companies, Alibaba and Tencent [49] (#2). The apps use a colour code to present the health condition of an individual—green implies people can travel freely, while yellow or red indicates they must report to the authorities. Users need to provide their name, national ID, and phone number to register and use the app to enter public places, e.g. the metro stations, supermarkets, and airports. The apps are mandatory and jointly developed by government departments and supported by data from health and transport
Table 1: Representative state-of-the-practice solutions from seven countries and five continents.

| ID | Country      | Name                        | Developer                              | Private/State | Technique | Architecture |
|----|--------------|-----------------------------|----------------------------------------|---------------|-----------|--------------|
| 1  | Australia    | COVIDSafe                  | Australian Department of Health        | State         | Bluetooth | Centralized  |
| 2  | China        | Health Code                | Alibaba                                | Private       | QR code   | Centralized  |
| 3  | Europe       | PEPP-PT*                   | International consortium               | Private       | Bluetooth | Centralized  |
| 4  | Europe       | DP3T                       | International consortium               | Private       | Bluetooth | Decentralized|
| 5  | Israel       | HaMagen                    | Ministry of Health                     | State         | Location  | Decentralized|
| 6  | Singapore    | TraceTogether              | Government Technology Agency           | State         | Bluetooth | Centralized  |
| 7  | South Korea  | Coronavirus Disease-19     | Ministry of Health and Welfare         | State         | Location  | Centralized  |
| 8  | USA          | Covid Watch*               | Stanford University                    | Private       | Bluetooth | Decentralized|
| 9  | USA          | Private Kit                | Massachusetts Institute of Technology  | Private       | GPS+Bluetooth | Decentralized|
| 10 | USA          | PACT*                      | University of Washington               | Private       | Bluetooth | Decentralized|

Table 2: User exposure.

| Solutions           | Generic | At-risk | Diagnosed | Architecture |
|---------------------|---------|---------|-----------|--------------|
| COVIDSafe           |         |         |           | Centralized  |
| Health Code         |         |         |           | Centralized  |
| PEPP-PT             |         |         |           | Centralized  |
| DP3T                |         |         |           | Centralized  |
| HaMagen             |         |         |           | Centralized  |
| TraceTogether       |         |         |           | Centralized  |
| Coronavirus Disease-19 |     |         |           | Centralized  |
| Covid Watch         |         |         |           | Decentralized|
| PACT                |         |         |           | Decentralized|
| Private Kit         |         |         |           | Decentralized|

Level I: No data is shared with servers or users.
Level II: Token shared with proximity users. Level III: Token shared with the server.
Level IV: PII shared with the server. Level V: PII is published to public.

The solutions that expose PII may not work well in countries with different societal norms. Thus, many western countries developed solutions with no PII related information exchange, e.g., PEPP-PT [57]. In PEPP-PT, an ephemeral user ID is implemented based on a seed randomly generated by a user device. Users will exchange ephemeral IDs, instead of encrypted PII messages, to record a proximity contact event, thus reducing the privacy exposure of diagnosed users to Level III where tokens are shared with servers.

Decentralized solutions. The second type of solution is decentralized, where: (i) the back-end server is only responsible for collecting the identifiers that was used by diagnosed users, e.g., the broadcast token, from diagnosed patients; and (ii) the health evaluation is conducted on users’ devices, locally. This design prevents the central server from knowing the infected person, and their physical proximity contacts.

Some decentralized systems rely on location information. For example, Hamagen (#5), an app provided by the Israeli Ministry of Health, obtains but does not share location data from the user’s phone and compares it with the information stored in a central server regarding the location histories of confirmed cases. As no data is shared before diagnosis, the exposure level of at-risk users are evaluated as Level I in Table 2. However, the diagnosed users will be notified and given the option of reporting their exposure to the Health Ministry by filling out a form; subsequently, their location trails are released to public.

Other Bluetooth solutions, e.g., DP3T [58] (#4), Covid Watch [54] (#8), and PACT [18] (#10), implement decentralized designs to allow users to download diagnosed anonymous identifiers from the back-end server and compare with local records to obtain their risk of exposure to the virus. The design paradigm reduces the exposure level of at-risk users to Level II and the level of diagnosed users to Level III in Table 2 as no PII is shared by users. Apple and Google have released the “privacy-preserving contact tracing” API, which can support building decentralized contact-tracing apps [2].

Another application, Private Kit [8] (#9), a decentralized solution developed by Raskar et al. [51], enables individuals to log their own location information. Particularly, Private Kit also allows Bluetooth broadcasts between users to enable direct notification between users. As the sharing of diagnosed users’ location trails and the broadcasts between users is privacy protected, we determine Private Kit’s user exposure levels to be the same as other Bluetooth-based decentralized solutions.
3 SECURITY VETTING

In this section, we consider the list of 34 contact tracing apps curated and summarised in Table 3. We downloaded the apps from Google Play Store and evaluated their security performance against the four vetting categories: (i) manifest weaknesses; (ii) general vulnerabilities; (iii) data leaks (with a focus on those that violate user privacy); and (iv) malware detection. We detail the list of issues considered in Table 4.

3.1 Methodology

An overview of our security vetting methodology is shown in Figure 1 and we describe the method used for selecting the apps for our investigation in Section 3.1.1. We perform: (i) static analysis, including code analysis and data flow analysis; (ii) dynamic analysis to detect malware.

3.1.1 Apps Selection. In order to curate a list of contact tracing apps, we first searched the keywords, e.g. “contact tracing”, “Covid”, “tracing coronavirus”, in Google Play Store. We also started with known official apps from countries, e.g. the COVIDSafe recommended by Australian government. After a contact tracing app is found, we assess its functionality by reading the app descriptions and select those with in excess of 10,000 downloads. Subsequently, we include the app into the set and look for new apps through the recommendation links in the app store, until there are no contact tracing apps found. We repeated this procedure one week later and finalised the list of 34 contact tracing apps summarised in Table 3 on 1 May 2020.

3.1.2 Static Analysis. We perform static analysis on the Android Package (APK) binary files. We first de-compile the APK of each app to its corresponding class and xml files. Then, we utilize the Mobile Security Framework (MonSF) [6] to perform code analysis and FlowDroid [15] for data flow analysis. Notably, we augment our static analysis with manual inspections to further increase the robustness of the vetting process. We detail our approach in Appendix A.

3.1.3 Dynamic Analysis. We rely on malware scanners to flag malicious artifacts in contact tracing apps. Concretely, we send the APKs to VirusTotal [12], a free online service that integrates over 70 antivirus scanners, which has been widely adopted by the research community [29, 42]. As shown in Table 4, the results of malware detection will identify the detected viruses, worms, Trojans, and other malicious content embedded in the apps.

3.2 Security Vetting Results

We next inspect the presence of security vulnerabilities among the 34 considered apps. Figure 2 shows the percentage of contact tracing apps that have security weakness found in our Code Analysis.

**Code analysis.** Figure 2 shows that the most prominent vulnerabilities extracted from the manifest weaknesses. We observed that 68% of apps do not set the flag allowBackup, which may enable a network attacker to implant man-in-the-middle (MITM) [5] attacks during network transmission.

Notably, during our manual review of the vetting results from MonSF. We found false positives in three results, i.e., Clear Text Storage, Saving Data in Temporary File, and SQL Injection. For example, in the application COVIDSafe, broadcast and channel identifiers, encryption algorithm names, and placeholders, which

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Table 3: Contact tracing apps considered in our analysis.

| Applications* | Country         | Downloads | Version |
|--------------|-----------------|-----------|---------|
| Coronavirus AlgÃľrie | Algeria        | 100K      | 1.0.3   |
| Stopp Corona  | Austria         | 100K      | 1.1.4.11|
| CoronaReport  | Austria         | 10K       | 2.9.5   |
| Coronavirus Australia | Australia   | 500K      | 1.0.2   |
| COVIDSafe     | Australia       | 1M        | 1.0.11  |
| BeAware Bahrain| Bahrain        | 100K      | 0.1.4   |
| Coronavirus Bolivia | Bolivia      | 50K       | 1.2.7   |
| Coronavirus - SUS | Brasil         | 1M        | 2.0.5   |
| COVID-19*     | Czech           | 10K       | 0.9.4   |
| Stop Covid    | Georgia         | 100K      | 1.0.461 |
| COVA Punjab   | India           | 1M        | 1.2.2   |
| CG Covid-19 ePass | India         | 500K      | 1.0.6   |
| West Bengal Emergency Fund | India | 10K   | 1.3     |
| Hamagen       | Israel          | 1M        | 1.1.2   |
| Stop COVID-19 KG | Kyrgyzstan    | 10K      | 0.3.137.325|
| MySejahtera   | Malaysia        | 500K      | 1.0.8   |
| SGS CORONA    | Mali            | 10K       | 0.0.6   |
| Nepal COVID-19 Surveillance | Nepal     | 5K        | 1.1.1   |
| Hamro Swasthya | Nepal          | 50K       | 1.3.2   |
| COVID Radar   | Netherlands     | 50K       | 1.1.2   |
| National Action Plan | Pakistan   | 50K      | 1.1     |
| Corona Map    | Saudi Arabia    | 50K       | 1.0.0   |
| TraceTogether | Singapore       | 500K      | 1.8.0   |
| NICD COVID-19 Case Investigation | South Africa | 10K | 1.16 |
| STOP COVID19 CAT | Spain        | 500K      | 1.0.2   |
| StopThespread COVID-19 | UK   | 100K      | 1.0.0   |
| Coronavirus UY | Uruguay        | 100K      | 2.2.3   |
| Private Kit   | USA             | 10K       | 0.5.19  |
| Contact Tracing | USA          | 10K       | 1.3.8   |
| Contact Tracker | USA          | 10K       | 2.0.2   |
| COVID-19      | Vietnam         | 100K      | 1.0     |
| NCOVI         | Vietnam         | 1M        | 1.5.3   |
| Vietnam Health Declaration | Vietnam | 100K | 1.0.12 |
| Bluelzone      | Vietnam         | 100K      | 1.0.1   |

*Note: apps were collected on 24 April 2020 and 1 May 2020 from Google Play Store.

Table 4: Security vetting categories.

| Vetting Category* | Security Issues |
|-------------------|-----------------|
| Manifest Weaknesses | Insecure flag settings, e.g. app data backup allowed Non-standard launch mode Clear text traffic |
| Vulnerabilities | Sensitive data logged SQL injection IP address disclosure Uses hard-coded encryption key Uses improper encryption Uses insecure SecureRandom Uses insecure hash function Remote WebView debugging enabled |
| Privacy Leaks | Trackers Potential Leakage Paths from Sources to Sinks |
| Malware Detection | Viruses, worms, Trojans and other kinds of malicious content |

*Note: security issues are summarized from FlowDroid (Privacy Leaks), VirusTotal (Malware), and MonSF (Manifest Weaknesses, Privacy Leaks, & Vulnerabilities).
are used to receive or query specific values but do not contain sensitive information, are stored as constant values. However, MobSF regards all constant string values as potential clear text storage. Some applications, e.g. Coronavirus UY (Uruguay), create template files while decompressing and loading multiple dex files in order to avoid the 64K reference limit [43]. Other applications, e.g. CG Covid-19 ePass (India), are able to scan other’s barcode and save it into temporary files in order to read the content. However, these behaviours are mis-regarded as temporary file leakage by MobSF. All these false-positives were removed through manual inspections from our further analysis.

Figure 2 shows that the most frequent weakness detected by static analysis is the “Risky Cryptography Algorithm”. Over 90% of apps use at least one of the deprecated cryptographic algorithms, e.g. MD5 and SHA-1. For instance, in the app MySejahtera (Malaysia), the parameters in WebSocket requests are combined and encrypted with MD5 which will be compared with the content from requests in the class Draft_76 in order to verify the validity of connections. Although this has been listed in the top 10 OWASP [7] mobile risks 2016, the results show that it is still a common security issue. Another frequent weakness is “Clear Text Storage” (files may contain hard-coded sensitive information like usernames, passwords, keys etc.). In class DataBaseSQL of COVID-19 (Vietnam) app, the password of SQLite database is stored in the source code without encryption; CG Covid-19 ePass (India) also hard-coded its encryption key in class Security.

In total, 20 trackers have also been identified, including Google Firebase Analytics, Google CrashLytics, and Facebook Analytics. Approximately 75% of the apps contain at least one tracker. As shown in Table 5, the most frequent tracker is Google Firebase Analytics which is identified in more than 70% of the apps. Notably, a research study [38] argues that TraceTogether using Google’s Firebase service to store user information may leak user’s privacy to third parties, such as Google. In the most extreme case, a contact tracing app, the Contact Tracing (USA), contains 8 trackers.

Data flow analysis. Figure 3 presents the flow of data between sources and sinks. This is counted by the number of source-to-sink paths found in each apps. The top sources of sensitive data are methods calling from Location and database. Cursor. These may obtain sensitive information from a geographic location sensor or from a database query. Most of the sensitive data will be transferred to sinks, such as Bundle, Service, and OutputStream, which may leak sensitive information out of apps. As discussed previously, sending sensitive information to the Bundle object may reveal sensitive data to other activities. Besides, developers usually utilize Log to print debugging information into Logcat [4] panel. However, human errors from developers can lead to mistakenly print sensitive data. Notably, we discover that some apps transmit location information through SMS messages. Considering Hamagen (Israel) as an example, location information is detected and obtained by a source method initialize(Context,Location,e) and then flows to a sink method where Handler.sendMessage(Message) is called. This is a potential vulnerability as malware could easily intercept the outbox of Android SMS service [15].

We also manually vet the FlowDroid results for false positives. In total, 60 out of 371 paths (16.17%) are false positives (results
which is recognized as a source. As country code is not confident-
tional and does not leak privacy, we consider this as a false-positive

Figure 3: Data flows detected between sources and sinks. Per-
centages indicate the fraction of flows originating at the sources (left) and terminating at the sinks (right).

presented in Figure 3 are excluding these false positives). There are mainly two categories of false positives. The first one is re-
lated to “Log” sinks where FlowDroid marks all log methods as
sinks, while some of them are not actually sensitive. For instance, in
TracTogether, error messages, such as SQLiteException from the
stack trace that occurs while data querying, will be logged by Log.e
method. This matches the keywords and is false-positively identi-
fied as a sink. Another example is, in Private Kit, while the status of
LocationProvider changes, geo-location data are read in func-
tion LocationListener.onStatusChanged. According to the app
source code, we found only the status values, including OUT_OF_-
SERVICE, TEMPORARILY_UNAVAILABLE, and AVAILABLE, are logged
by Log.v or Log.d, instead of the logging of the geo-location data.
Most of the false positives we find fall into this category. Another
type of false positive results come from preference leakage detection.
For example, the app STOP COVID19 CAT (Spain) stores country
code (e.g. UK and AU) by invoking Locale.getCountry method
which is recognized as a source. As country code is not confidenti-
al and does not leak privacy, we consider this as a false-positive
source.

Malware detection. We discovered only one application, Stop
COVID-19 KG (Kyrgyzstan)\(^2\), containing malware. Two risks are
identified: a variant Of Android/DataCollector.Utilcode.A and
an Adware (0053e0591). This is also aligned with the finding of
COVID-19 apps’ threats [55]. Consider the limited spreads of Stop
COVID-19 KG (about 10,000 downloads), we conclude that the vast
majority of contact tracing apps we collected from Google Play
Store are free of malware. However, the rise of contact tracking apps
including passwords and identity information, in a debug-enabled
manifest setting, and some apps have more trackers identified.

Table 6: Results of regression testing of apps.

| Application      | Version | Issues Patched                  |
|------------------|---------|---------------------------------|
| TraceTogether    | 2.0.15  | ✓ Disabled Allow Backup;        |
|                  |         | ✓ Fixed potential privacy leakage. |
| STOP COVID19 CAT| 2.0.3   | ✓ Fixed Insufficient Random issue as they do not use Microsoft package anymore; |
|                  |         | ✓ Fixed potential privacy leakage; |
|                  |         | ✓ Allows clear text traffic in manifest; |
|                  |         | ✓ New tracker detected: Google CrashLytics. |
| Mysejahtera      | 1.0.19  | ✓ Fixed the incorrect launch mode of an activity; |
|                  |         | ✓ Removed three trackers: Google Analytics, Google CrashLytics, and Google Tag Manager. |
| BlueZone         | 2.0.2   | ✓ Fixed potential privacy leakage. |
| COVA Punjab      | 1.3.11  | ✓ New WebView weakness is detected, which could enable popup windows; |
|                  |         | ✓ New potential privacy leakage path found; |
|                  |         | ✓ New tracker detected: Google CrashLytics and Google Ads. |
| Coronavirus UY   | 4.3.2   | ✓ New tracker detected: Google CrashLytics. |
| Contact Tracer   | N/A     | ✓ No longer available in Google Play Store |

\(\ast\) Note: new versions were collected on 24 June 2020 from Google Play Store.

longer available in Google Play Store (see Table 6). Meanwhile, new
vulnerabilities are identified in the updated versions of several apps.
For example, COVA Punjab (India) enables popup window in Web-
View setting, STOP COVID19 CAT (Spain) allows clear text traffic
in manifest setting, and some apps have more trackers identified.

3.3 Case Studies

From our curated list of 34 apps, we select four typical app to further
highlight key lessons we can learn with respect to security and
privacy risks. The case studies are based on TraceTogether, DP3T,
Private Kit, and COVIDSafe.

TracTogether. According to the static analysis results, root detec-
tion [27] has been implemented, which potentially prevents SQL
injection and data breaches, thereby reducing the the risk to a cer-
tain extent. For example, in o/C3271ax.java, root detection logic
is implemented by detecting the existence of specific root files in
system, e.g. /system/app/Supersuser.apk and /system/xbin/su;
by assessing their integrity, the application can detect whether a
device is rooted and subsequently block users from either login or
opening the applications.

However, TraceTogether also includes a third-party customer
feedback library, Zendesk SDK, in which the remote WebView
debugging is enabled. This potentially allows attackers to dump the
content in the WebView [17]. When a user inputs confidential data,
including passwords and identity information, in a debug-enabled
WebView, attackers may be able to inspect all elements in the web
page by using remote debug tools [34]. Fortunately, according to
the static analysis, the only WebView with debugging mode enabled
is to display articles; therefore, does not contain confidential data.

Security guidance 1: Never leave WebView with debugging
mode enabled in the App release.

\(^2\)https://play.google.com/store/apps/details?id=kg.cdt.stopcovid19

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**DP3T**. According to the static analysis, DP3T’s database is not encrypted, and data is saved in plain text. In contrast to TraceTogether, the app does not implement any root detection capabilities. This means that a malicious app could possibly access the database directly and manipulate the database containing COVID-19 contact records. Potentially, an adversary could spread false-positive.

**Security guidance 2:** To protect the database from being dumped and prevent data breaches, a solution should:

1. Implement database encryption [11] and
2. Enable root detection [1] and confidential data protection [10] at application startup.

In addition, as the database records timestamps and contact IDs, the leakage of the database from a root device infected by a mobile system virus can be exploited to mount linkage attacks by adversaries [9]. If enough data in a region were collected by attackers, contact IDs and timestamps in the database can be used to analyze movements by comparing data and device owners may be identified through a linkage attack [63].

**Private Kit.** Similar to DP3T, Private Kit does not encrypt the database and contains plaintext data. Besides, the app creates temporary JSON files to store user’s location data. Without any encryption and root detection, the temporary JSON file can be dumped from root devices; thus increasing the risk of privacy leakage.

**Security guidance 3:** To prevent potential data breaches, tracing records and confidential data must not be stored in temporary files in plain text.

**COVIDSafe.** According to our experiments, COVIDSafe 1.0.11 stores all tracing histories, including contacted device IDs and timestamps, into SQLite database with plain text. Since the application does not implement a root detection logic, tracing histories may be leaked from root devices and potential Linkage Attacks can be implemented [63]. However, in the latest version, COVIDSafe fixed this issue by encrypting local database with a public key.

Mussared and McMurtry [33] discussed long-term device tracking and some other privacy-related attacks, substantiated as CVE-2020-12856. In addition, due to the use of Generic Attribute Profile (GATT), the phone model name and the device name are shared between users. Although this information may not be considered as PII, it could be set by users in a form of “Firstname Lastname’s Phone Model”, e.g., “Jim Green’s Pixel 2”, which allows an attacker to easily re-identify and track a user as this information will be continuously broadcast. A practical demonstration of extracting such information is available online. Furthermore, a bug is found when a phone is locked; if its temporary ID is expired, the phone cannot provide a new ID to devices in the proximity [46]. In such a situation, a user will not be recorded by other users and will not receive an at-risk alarm if someone she contacted with is diagnosed. Considering that it is usual to keep a phone locked, this may lead to serious false-negatives.

**Security guidance 4:** To protect the system against false-negatives caused by malfunction, thorough and comprehensive testing must be carried out. In particular, the situations, such as the mobile phone is locked and app are running in the background, should be seriously considered.

Besides aforementioned issues, in accordance with the report released on 14 May 2020 [45], several vulnerabilities, such as CVE-2020-12857 and CVE-2020-12858, have been fixed. In CVE-2020-12857, the COVIDSafe app improperly catches GATT characteristic values, i.e., TempID, for a long time until a successful transaction takes place, instead of clearing the values periodically. As the data could be read by a remote device, if an attacker never completes the transaction, he will always obtain the same TempID from a user, which may enable the long-term tracking of the user. However, this issue has been fixed by removing the entry to catch when a device is disconnected. The root cause of CVE-2020-12858 is because of the generation and use of the unchanged advertising payload, which means that an attacker is able to track a device by identifying its advertising payload. In the latest update, the payload will not be cached.

### 4 PRIVACY RISK ASSESSMENT

In this section, we describe the privacy analysis we conducted on the 10 selected contact tracing solutions in Table 1 to assess their protection against potential privacy breaches under our threat model.

#### 4.1 Threat Model

We consider four attackers in our threat model in addition to the user groups defined in Section 2.1:

**Application users.** Those who install contact tracing applications on their mobile phones will receive information about COVID-19, e.g., an at-risk alarm. A regular user may reveal their private information, e.g., name, gender, phone number, national ID, home address, and location history, to the contact tracing systems, as well as discover other users’ private information from the system—public information or broadcasts from other users.

**Health authorities.** The actors are responsible for diagnosing infections and collecting health information from Application users. May learn or deduce private information about at-risk users. Health authorities will also help the diagnosed users record or upload information to the contact tracing system.

**Governments.** These actors work with technology providers and are often responsible for operating the contact tracing system. They may access the data stored in a central server. In our threat model, we suppose the Government (and even the cloud operator) is “untrusted”, that is, they may use the collected data for purposes beyond the pandemic.

**Malicious adversaries.** These adversaries have access to local app information. They follow the defined algorithms, but wish to learn more than the allowed information. They may have the capability to access the local log of contact tracing applications, but hacking the back-end server or another user’s device is out of the

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1. [https://twitter.com/wabzqem/status/1257547477542027270](https://twitter.com/wabzqem/status/1257547477542027270)
4.2 Potential Attacks

As discussed previously, the privacy of users is hard to preserve in a contact tracing system. To introduce potential privacy risks, we will let Alice be an at-risk user, and let Bob be a diagnosed user who has been in contact with Alice. Mallory will be a malicious attacker, and Grace will be the government server (or other authority). Here we discuss four potential attacks. According to our threat model in Section 4.1, if an attacker is not able to re-identify a user or inject fake reports to a contact tracing system through a specific privacy attack, we try to determine the system as well-protected to prevent such an attack; otherwise, the system will be considered as at-risk.

The vetting results are summarized in Table 7.

**Linkage attacks by servers.** In centralized systems, the major privacy concern is metadata leakage by the server. For example, in Coronavirus Disease-19 website, TraceTogether and COVIDSafe, a central server is used to collect PII information and to evaluate at-risk individuals. Consequently, Grace will be able to collect a large amount of PII, such as names, phone numbers, contact lists, post code, home addresses, location trails. Therefore Grace is able to deduce the social connections of Alice. Even for PEPP-PT, a centralized Bluetooth system with solutions to avoid PII collection, the re-identifiable risks still exist. For example, from the server side, Grace is able to link ephemeral IDs to the corresponding permanent app identifier and thus trace Alice based on IDs observed in the past, as well as tracing future movements. Thus, no centralized solutions in Table 1 can prevent linkage attacks by the server.

In contrast, for decentralized Bluetooth solutions, Alice’s privacy is protected as her PII will not be sent to a central server by a diagnosed user and her health status is evaluated on her own device. Thus, decentralized Bluetooth systems are able to protect users’ privacy against linkage attacks by the server. However, in location-based decentralized systems, e.g., Hamagen, the server learns users’ location trails.

**Linkage attacks by users.** Linkage attacks, performed by Mallory, try to re-identify Alice or Bob. As discussed previously, in contact tracing systems that directly publish users’ PII, e.g., Coronavirus Disease-19, Hamagen, and Health Code, Bob is at the risk of privacy leakage. For example, in Coronavirus Disease-19, Mallory could be able to re-identify Bob as he will know Bob’s gender, age, and location history from public information.

The other 7 systems listed in Table 1 further rely on information exchange between users. In number of the apps, e.g., DP3T, which implement an ephemeral ID design, Mallory is still able to identify Bob using more advanced attacks. For example, if Mallory places a Bluetooth receiver near Bob’s home or working place and ensures that the device will only receive Bluetooth broadcasts from Bob. Once Bob is diagnosed, Mallory will receive an at-risk alarm and immediately acknowledge that the infected patient is Bob. In addition, Mallory can log the timestamp and the received ephemeral ID when in contact with Bob. Once Bob is diagnosed, Mallory is able to trace back the source of recording and re-identify Bob and potentially infected users. Similar attacks were described as Paparazzi Attack and Nerd Attack in an analysis of DP3T [59]. Note that Mallory is able to extend such attacks to Sybil attacks to enable the identification and the tracing back of multiple targets at the same time. Even worse, if Mallory distributes multiple broadcast receivers, which could be also considered as a Sybil attack, in a large area with some layout, e.g., honeycomb, they could even trace the movement of Bob by tracing the records on each device. Thus, none of the 10 typical solutions can fully protect users’ privacy against linkage attacks by Mallory.

**Privacy guidance 1:** To protect users’ privacy against linkage attacks by a server, a contact tracing solution should:

1. Avoid sharing PII information with central points or
2. Implement a decentralized design.

**Privacy guidance 2:** To protect users’ privacy against linkage attacks by an adversary, a solution should:

1. Ensure privacy protections exist for any published data.

**False positive claims.** In some systems, such as Coronavirus Australia, Bob can register as infected and upload data through the contact tracing app to the server, which enables Alice to receive an at-risk alarm. However, if Mallory exploits such a mechanism and registers as a (fake) infected user, Alice will receive a false-positive at-risk alarm, which may cause social panic or negatively impact evidence-driven public health policies. Most solutions mitigate this issue by implementing an authorization process, i.e., Bob is only permitted to upload data after receiving a one-time-use permission code generated by the server. Without the permission code, Mallory is not allowed to claim they are infected and Alice will always receive a true at-risk alarm. Only two solutions, i.e., DP3T and PACT [18], have no authorization process implemented.

**Privacy guidance 3:** To protect a system against false-positive-claim attacks, a solution should establish an authorization process.

**Relay attacks.** To apply such an attack, Mallory could collect existing broadcast messages exchanged between users, then replay it at another time or forward it through proxy devices to a remote location and replay the messages. Due to the lack of message validation in solutions that utilize information broadcasts, a user will not be able to determine whether a received broadcast is from a valid source or from a malicious device. Any received broadcast will be recorded as a contact event, even though no actual contact exists. A malicious attacker can potentially redirect all the traffic from one place to another, resulting in a targeted area being incorrectly locked-down by replaying fake information.

For example, suppose Mallory records the broadcasts from Bob and then replays it hours later, or transmits it to a remote location and replays the messages to Alice. Alice’s device, although not actually being in contact with Bob, will receive and record the replayed broadcast in its local log. Once Bob is diagnosed, Alice will

*The combination of man-in-the-middle and replay attacks are henceforth referred to as a relay attack.*
As discussed in Section 4, a contact tracing application should preserve the privacy of generic and at-risk users. Although the diagnosed user may reveal their privacy to health authorities, we should not release this data to the public. Furthermore, we argue that a contact tracing solution should focus on tracing anonymous daily routines or occasional contacts, instead of close contacts. Here we propose a venue-accessing-based solution, VenueTrace, to overcome privacy risks. We will first describe the framework of this solution and assess its privacy performance as well as its limitations.

Table 7: Privacy protections against the attacks.

| Solutions   | Linkage-Server | Linkage-User | False-Claim | Relay |
|-------------|----------------|--------------|-------------|-------|
| CovidSafe   | ●              | ●            | ●           | ●     |
| Health Code | ●              | ●            | ●           | ●     |
| PEPP-PT     | ●              | ●            | ●           | ●     |
| DP3T        | ○              | ●            | ●           | ○     |
| HaMagen     | ●              | ●            | ○           | ○     |
| TraceTogether| ●              | ●            | ●           | ○     |
| Coronavirus | ●              | ○            | ●           | ○     |
| Disease-19  | ○              | ●            | ○           | ○     |
| Covid Watch | ○              | ●            | ○           | ●     |
| Private Kit | ○              | ○            | ●           | ●     |
| PACT        | ○              | ○            | ●           | ●     |

Q: the system is well protected; O: the system is at-risk

receive an at-risk alarm even though she has never been in contact with Bob. Such an attack will falsely enlarge the contact range of Bob and create a large amount of false-positive alarms, which may cause panic among citizens. Solutions that do not utilize information broadcasts, such as Coronavirus Disease-19 and Hamagen, can avoid relay attacks.

In DP3T, a solution is provided to limit the replay attack by including temporal information in the broadcast ephemeral identifiers. However, it cannot effectively prevent replay attacks occurring at the same moment. Another promising solution is to use an ambient physical sensing approach, e.g., ambient audio. This has been shown to secure proximity detection [26, 56] by comparing the ambient information embedded in the broadcast messages with the local ambient. It allows a receiver to validate whether the source is nearby as the range of Bluetooth broadcast is generally within 50 m.

Privacy guidance 4: To protect a system against relay attacks, a solution should:
(1) Either avoid utilizing information broadcast or
(2) Implement a validation approach.

5 OUR RECOMMENDATIONS

As discussed in Section 4, a contact tracing application should preserve the privacy of generic and at-risk users. Although the diagnosed user may reveal their privacy to health authorities, we should not release this data to the public. Furthermore, we argue that a contact tracing solution should focus on tracing anonymous daily routines or occasional contacts, instead of close contacts. Here we propose a venue-accessing-based solution, VenueTrace, to overcome privacy risks. We will first describe the framework of this solution and assess its privacy performance as well as its limitations.

5.1 Our Privacy-by-Design: VenueTrace

The architecture of VenueTrace contact tracing consists of the following modules as described in Figure 4.

Bluetooth broadcaster in public places. Instead of broadcasting from each user’s mobile phone, the VenueTrace proposes utilizing Bluetooth broadcast devices installed in public places, e.g., restaurants, movie theaters, working places, and public transport hubs and stops. This is in contrast to most existing Bluetooth solutions that rely on human-to-human contact. To facilitate contact tracing, at setup, each broadcast device will register its MAC address to a back-end server and get a unique VenueID which will be broadcast through Bluetooth at every Time Interval T. Hence, users are not required to broadcast information.

Applications installed in the user’s phone. For every VenueID broadcast by a device in its proximity at time t, after receiving the broadcast VenueID, a pair (ID, t) will be created and a timer will be started in the user application. If a user receives the VenueID after T again, the user stores a tuple which satisfies the following:

(ID, t_{start}, t_{end}), \quad \text{where } t_{start} - t_{end} \geq T, \quad (1)

where t_{start} is the first timestamp of the received the broadcast VenueID in the local storage for 14 days; t_{end} is the last timestamp of a period over which a user continuously received VenueID. For example, if T is set to 10 minutes and Bob stays in a public place for more than 30 minutes, he will at least receive the broadcast for three times, e.g., t_1, t_2, and t_3. The application will record the tuple (ID, t_1, t_2) in local log, where t_3 - t_1 = 20 minutes, indicating that he stayed in a public place for at least 20 minutes.

Once Bob is diagnosed, with his consent, he will receive a permission code from the health authority, then Bob can upload his log (ID_{Bob}, t_{start}, t_{end}) and the permission code to the back-end server. To ensure the security of data transmission, the data will be encrypted with the Public Key of the back-end server. Every twenty-four hours, Alice will download logs in a format of (ID_{Server}, t_{start}, t_{end}) from the back-end server and a record match and an evaluation will be conducted locally. A local record, i.e., (ID_{Alice}, t_{start}, t_{end}), is considered as matched if the following conditions are true.

ID_{Alice} = ID_{Server}

(t_{start} - t_{end}) \leq (t_{start} - t_{end}), \quad (2)

which indicates that Alice has been in a public place during the period (t_{start}, t_{end}) and may have been in an at-risk environment. If there is a match in Alice’s local log, Alice’s device will generate an at-risk alarm.

Decentralized back-end server. The back-end server supports the activities of (i) registering the Bluetooth broadcaster by storing its MAC addresses and VenueIDs; (ii) generating and authorizing permission codes to health authorities; (iii) publishing the public key and deciphering the data uploaded by diagnosed users with its private key; (iv) validating the received VenueIDs and permission code; and (v) publishing at-risk information to regular users in the format of tuples (ID_{Server}, t_{start}, t_{end}).

ID_{Server} = ID_{Bob},

t_{start} = t_{start} - T - \text{random},

t_{end} = t_{end} + \delta + \text{random}', \quad (3)

where the at-risk time interval is extended based on Bob’s record by T in the upper limit and δ in the lower limit. A typical δ could be set to 12 hours to ensure that Alice will be informed that she has been in an at-risk venue where she may have touched a virus-contaminated surface or inhaled airborne droplets, even though she has never been in close physical contact with Bob. We could also further extend the visiting duration with random noise to blur the timeline. For example, if Bob visited a public place from 9 am to 10 am,
the released infected duration could be from 8:30 am to 11:15 pm, where $T = 5 \text{ mins}$, $\text{random} = 25 \text{ mins}$, $\delta t = 12 \text{ hours}$, $\text{random'} = 75 \text{ mins}$. Considering the time-related functionality of a public place, this duration could be further capped.

5.2 Defending Against Attacks

A major flaw in many implemented and proposed applications is that they cannot fully guarantee user privacy when using user-provided data. Of the applications discussed in this paper, this issue is particularly prevalent with centralized solutions, e.g. TraceTogether, as they may suffer from linkage attacks not only by users but also by the server. However, any application that requires symptom reporting from its user base could potentially be vulnerable, as discussed in Section 4.

Decentralized computation. Compared to centralized systems, our solution has the inherent advantage of decentralized systems, that is, users’ privacy is not exposed to the server. The back-end server will only receive the timestamp and VenueID of a public place that is visited by diagnosed users. Supposing a malicious attacker successfully extracts data from the back-end server, he is still not able to link the information to any location or users as there is no location information stored in the server. Thus, the user privacy is protected against the linkage attack by a server.

Coarse-grained location. Furthermore, in contrast to location based solutions (e.g. Hamagen) our solution does not utilize GPS information as Bluetooth is more advantageous than GPS signals in high risk indoor environments. However, considering the extension and blurring in timelines, the back-end server will only receive and publish venue IDs with at most coarse-grained location information. In addition, our solution overcomes the limitation of location-based tracing by installing the broadcaster in public venues and transports in contrast to user devices.

No token exposure. Many Bluetooth-based decentralized systems provide a privacy preserving solution by only sharing the temporary tokens between users. However, it is still amenable to linkage attacks by users. Compared to other decentralized solutions, our solution further preserves user privacy as no information is exchanged between users. Consequently, our system is immune to linkage attacks by users. In the worst case, the attackers may physically visit public places and record the venue IDs, then they may link venue IDs to locations. After an at-risk alarm, the attacker may perceive where a diagnosed user appeared. However, the attackers still does not have enough information to re-identify the infected individuals, unless they log all persons having appeared in multiple public places for a long period and is able to infer the persons matching the timeline. Thus, without information shared between users, the linkage attack by users and real-time movement tracks are impossible.

False positives. Aside from real people misreporting their symptoms, applications that rely on diagnosed users’ information are at risk of malicious false-positive claim. For location-based applications, these attacks are very effective. For a GPS based system, an attacker could spoof a series of GPS coordinates to an app. If no authentication measures are implemented, uploading such spoofed GPS data to the server can cause potential havoc across the system. This scenario, in retrospect, emphasizes the design of permission code in our recommendation. A user is allowed to register as infected only after being authorized with a permission code, which prevents false-positive claims.

Further considerations. To protect users’ privacy against relay attacks, the VenueTrace solution can be updated by including blurred location information in broadcasting. As a relay attack will replay a VenueID in another remote place and thereby expanding the broadcast range and causing false-positive alarms, we can distinguish fake broadcasts by combining the location of broadcasters in the broadcast message. When the user receives a broadcast, the application can parse out the location of the broadcaster and compare it with the location of a receiver to filter those bounded by a distance, e.g. greater than 1 km. This allows eliminating such replay forgeries. As the original intention of the VenueTrace solution is to prevent the back-end server from obtaining locations of broadcasters and users, we can only add vague location information to the broadcast information, such as adding a 1 km error, to prevent the relay attack while preserving users’ privacy. However, this, to some extent, weakens the location privacy protections of our solutions.
6 RELATED WORK

Location tracking. Recent works have explored extracting location information from mobile apps [50, 53, 60, 62]. For instance, Xue et al. [61] presented a supervised machine learning methodology to localize users without any reverse engineering of the app. In our vetting, we considered such situation as a linkage attack by users, which extended the scope to also include tracking via Bluetooth. Although it may cost much to build up a large-scale Bluetooth broadcasting and receiving network, e.g., a honeycomb layout, to apply a movement tracking attack, it is still a considerable risk of privacy leakage.

Contact tracing tools analysis. Several recent works have focused on the evaluation and analysis of contact tracing applications. Just 10 days after TraceTogether launched, Cho et al. [20] presented a constructive discussion of potential modifications to encourage community efforts to develop solutions with stronger privacy protection and argued that privacy is a central feature of mobile contact tracing apps. One week later, Vaudenay [59] analyzed the DP3T solution and pointed out that some privacy protection measurements by DP3T may have the opposite effect. Gvili [25] presented a security analysis of the Bluetooth and cryptography specifications published by Apple and Google [30, 31], arguing that significant risks may be introduced by this solution. Other works [39, 41] conducted a review of the centralized and decentralized solutions and proposed contact tracing using a zero-knowledge protocol. He et al. [28] inspect the expansion of COVID-19 related apps more broadly, identifying the presence of malware.

Our work. In contrast to aforementioned works, our research not only focuses on the analysis of one solution or the comparison between centralized and decentralized designs, but also conducts a security and privacy vetting on multiple state-of-the-practice approaches. Concretely, we aim to extract security and privacy guidance from various solutions and propose more practical protection of individual security and privacy.

7 CONCLUDING REMARKS

This paper has conducted a security analysis of 34 contact tracing applications and evaluated the privacy performance of 10 solutions. The results show that security risks remain; such as using deprecated cryptographic algorithms, storing sensitive information in clear text, and allowing permissions for backup. Thus, we recommend that the reported vulnerabilities be patched as soon as possible, although we appreciate that developers may prioritize the speed of product release to counter the pandemic. That said, the majority of patches are straightforward. For example, over 70% of developers still use insecure hash functions such as SHA-1 and MD5, or storing sensitive information in clear text. Further, to ensure security and remove potential vulnerabilities, code should be released for public review.

Our analysis has shown that protecting privacy is more challenging, particularly as this must be balanced against the urgency of the pandemic. To the best of our knowledge, there are no solutions that can protect users’ privacy against all potential attacks. Besides the solutions that collect private information, the results of our privacy vetting indicates that most of the contact tracing apps are potentially vulnerable to malicious privacy attacks. We limit our scope to software vulnerabilities and privacy leakage. Examining Bluetooth Low Energy and network traffic originating from contact tracing apps are worth further exploration. Another future avenue is to examine any vulnerabilities associated with iOS counterparts.

To overcome a number of these issues, we have proposed a privacy-preserving contact tracing design, termed VenueTrace. The proposed recommendation has a decentralized architecture in which no information is exchanged among users and no location and identifiable information will be exposed to the server. However, just as with other apps, it is impossible to address all potential risks, e.g., our solution is similarly vulnerable to the relay attack; a solution requires compromising the privacy of our approach. We hope our study can inform and aid the software industry to design, develop, and deploy more secure (and privacy-preserving) contact tracing apps whilst allowing citizens to use contact tracing apps with more confidence in the capability of the apps to protect their security and privacy.

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APPENDICES

A STATIC ANALYSIS

Code analysis. MobSF is a state-of-the-art and open source penetration testing, malware analysis and security vetting framework [16], which flags vulnerabilities in code.

For context, MobSF works in the following way. The de-compiled AndroidManifest.xml file is first parsed to extract essential information about the application, such as Permission, Components, Intents. Then, the system assess requested permissions by the application and examine whether all Components (e.g. Service, Receiver, Activity, Provider) are protected by at least one permission explicitly requested in manifest file. Other attribute configurations, such as the allowBackup, debuggable, and networkSecurityConfig flags, will also be checked.

The class files are subsequently parsed via a Sensitive Data Match module, which utilizes keyword matching, e.g. “password” and “secret”. The Method Extraction module matches methods in class files with pre-defined rules to extract vulnerable methods. For example, if a method contains the keyword .hashCode(), it will be considered as using Java Hash Code, a weak hash function that should not be used in a secure cryptography implementation. However, as a weakness could be defined in third-party APIs, the vulnerable method may never be executed during run-time. To address this, the Determining vulnerable Calls module will vet whether a vulnerable method is actually called and assess whether the sensitive data is accessed. The system will record all the vulnerabilities listed in the Manifest Weaknesses and Vulnerabilities categories in Table 4. Further, the trackers in apps, e.g. Google Firebase Analytics, Facebook Analytics, and Microsoft Appcenter Analytics are detected by the Tracker Detection module and will be recorded in the Privacy Leaks category in Table 4.

The vetted vulnerabilities include SQL injection, IP address disclosure, hard-coded encryption keys, improper encryption, use of insufficiently random values (CWE 330) [3], insecure hash functions, and remote WebView debugging is enabled. We detail the manual inspections adopted subsequently in the vetting process in Appendix B and limitations to the code analysis vetting methods in Appendix D.

Data flow analysis. We conduct a data flow analysis using FlowDroid [15] to screen out high risk privacy leaks. Such data flow analysis extracts the paths from data sources to sinks, and the statements transmitting the data outside of the application. We use the sources and sinks inferred by SuSi project [52] which defines sources as calls to resource methods, e.g. getLatitude() and database. Cursor.getString(), while sinks are methods that may leak sources, e.g. Log.e() and Bundle.putAll().

FlowDroid searches the application for lifecycle and callback methods and then generates a call graph. Starting at the detected sources, the analysis tracks taints by traversing the call graph. If private data flows from a source to sink, it indicates that there is a risky privacy leak path. To remove false-positives, we conduct a backward flow analysis. If the vulnerable code is reachable, we determine it is a valid privacy leak. For example, if we find there is sensitive data that flows into a sink (e.g. Bundle, Log output, SMS) unauthorized users can access, we will trace it backwards to its source and confirm whether the source is reachable. If reachable, we consider it as a privacy leakage. Similar to the code analysis phase, we also conduct a manual inspection described in Appendix C. We describe the limitations to the vetting method in Appendix D.

B CODE ANALYSIS: MANUAL INSPECTIONS

To increase the accuracy of the vetting results, we manually verified the testing results of MobSF. First, considering that MobSF mainly relies on keywords and sentences matching in APIs, we check the rules defined in MobSF’s source code. Then, we collect rules with weak keywords defined. For example, if a rule only uses Log.v or System.out.print to find “sensitive data logging”, without checking whether the data is sensitive, we consider this is a weak rule. We automated the extraction of all Java files which are identified by these weak rules for manual inspection. Finally, we removed the false-positive cases from the testing results.

C DATA FLOW ANALYSIS: MANUAL INSPECTIONS

For data flow taint analysis, we manually review the FlowDroid results of all 34 apps. Since all APK files have been decompiled by MobSF, sink paths in XML reports generated by FlowDroid are closely contrasted with decompiled source codes in order to identify false-positive cases. First, sink paths are picked out to analyze the possibility of potential leakage. If any of these paths are suspected to be false-positive cases, we load source codes decomplied by MobSF in Visual Studio Code [13] and use its global search feature to find invoked methods mentioned in suspected sink paths. Finally, after analyzing the logic from source code, false-positive cases are confirmed.

D THREATS TO VALIDITY

Potential limitations to our methodology. Considering that both the core mechanisms of MobSF and FlowDroid heavily rely on keywords matching, a potential cause of false negatives is largely due to the scope of keywords. Concretely, in MobSF, there may exist vulnerabilities not defined in analysis rules. Similarly, in our data flow vetting, as we utilize the sources and sinks extracted by SuSi project, there may exist sensitive leakage that does not match any sources or sinks or that is not detected. We aim to improve the false negative by updating the rules and keywords database of MobSF and FlowDroid in future avenue. Currently, our vetting focuses more on the identified vulnerabilities and privacy leakage paths.