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Social Interaction Tracking and Patient Prediction System for Potential COVID-19 Patients

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***Abstract*—Coronavirus disease 2019 (COVID-19) virus is an infectious disease which has spread globally since 2019, resulting in an ongoing pandemic. Since it is a new virus, it takes some time to develop a vaccine against it. Until then, the best way to prevent the fast spread of the virus is to enable the proper social distancing and isolation or containment to identify potential patients. Since the virus has up to 14 days of the incubation period, it is important to identify all the social interactions during this period and enforce social isolation for such potential patients. However, proper social interaction tracking methods and patient prediction methods based on such data are missing for the moment. This paper focuses on tracking the social interaction of users and predict the infection possibility based on social interactions. We first developed a BLE (Bluetooth Low Energy) and GPS based social interaction tracking system. Then, we developed an algorithm to predict the possibility of being infected with COVID-19 based on the collected data. Finally, a prototype of the system is implemented with a mobile app and a web monitoring tool. In addition, we performed a simulation of the system with a graph-based model to analyze the behaviour of the proposed algorithm and it verifies that self-isolation is important in slowing down the disease progression.**

***Index Terms*—Internet of Things, Bluetooth Low Energy, GPS, COVID-19, SARS-CoV-2, Contact Tracing Algorithm, Infection Prediction**

I. Introduction

A new epidemic has emerged since late December 2019 from Wuhan, China which is caused by Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), and the disease caused by this virus was named as COVID-19 by the World Health Organization [1]. With the outbreak of this disease to a pandemic, the health systems encounter a major problem of overwhelming the patients and it could cause a great risk to the health of these patients since the healthcare systems may exceed their capacity to treat them properly. Early identification of potential COVID-19 patients via contact tracing leads to fast isolation and ultimately contributes to slow down the spread of the disease and flatten the patients' curve.

However, the manual contact tracing of a positive COVID-19 case needs the effort of many personnel including health workers and typically takes up to three days per case [2]. Moreover, the following issues are identified in existing systems.

First, it is important to identify all social interactions during the incubation period of 14 days and enforce social isolation for such potential patients. Therefore, there is a requirement to identify these social interactions. However, in this case, the solely GPS based solutions are identified to be inaccurate as they do not work indoors. Second, there is no proper social interaction based infection prediction method available due to the inability to track and obtain the past interactions of patients accurately. Third, healthcare workers are at a high risk of getting infected with COVID-19 virus, since they cannot identify the COVID-19 carrier without testing them. Finally, there is no proper method to identify the true group of people that need to be tested for infection. The random or testing with less information will be a waste of time, energy and money. Besides, some of the patients will not be identified.

Several BLE based contact tracing systems were developed recent past [3]–[6]. However, none of these systems are capable to provide social interaction based infection prediction to solve the above issues. To address these challenges, we designed a BLE and GPS based social interaction tracking system using a mobile app that can collect information about the nearby phones. Based on the received signal strength, it records the proximity of other phones and interaction duration. The collected information will get uploaded into the cloud with the GPS location (optional) and the timestamp. We also formulated a social interaction based infection prediction algorithm to calculate the COVID-19 infection probability by analysing the uploaded data to the cloud. An automatic alerting mechanism is designed to indicate critical events such as the identification of high probable COVID-19 patients. The prototype of the proposed solution is implemented and the efficiency of the proposed prediction mechanism is compared with a real COVID-19 patient data set.

The remainder of the paper is organized as follows: The related work is presented in section II. In section III, the system architecture is described and in section IV system implementation details are discussed. Section V gives the experiments and results. Finally, the paper concludes with the conclusion and future works in section VI.

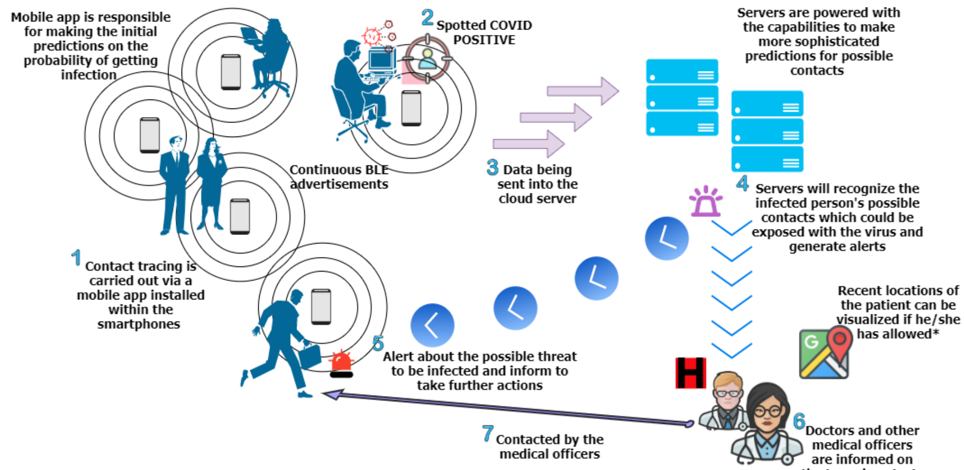


Fig. 1: Proposed System Architecture

II. Related Work

With the COVID-19 pandemic, several leading tech companies and government organizations have started working on the development of contact tracing systems to detect possible contacts with COVID-19 patients while protecting their privacy. They have followed several guidelines to achieve their goals associated with these developments.

Among them, Google and Apple are collaboratively developing a system with a contact tracing app that is available to both Google Android and Apple iOS platforms. In their work, each mobile will ping each other continuously via Bluetooth and if two mobiles have remained within the range of each other, both will record the ID of the contacted mobile accordingly [3]. With this app specifications, users have to manually transmit the contact logs to the servers. In this case, if he or she becomes positive for the COVID-19, it may become problematic if someone is not informing the authorities about the disease.

MIT (Massachusetts Institute of Technology) has presented a similar work with the collaboration of many other researchers. Their system relies on Bluetooth signals and is consisting of a kind of random strings of numbers, equate to “chirps” and these could be heard and remembered by the nearby smartphones. Here, each smartphone is supported by an application and each smartphone remembers what has been broadcasted and what was heard from the outside. Users will manually transmit the list of chirps into the server after a user becomes positive for COVID-19 and alerts will be sent to the possible contacts of the user accordingly [4].

Furthermore, the Singapore SGUnited, GovTech, and the Ministry of Health have provided another solution namely “TraceTogether” for contact tracing of COVID-19 patients using Bluetooth by following similar principles as mentioned in above two developments [3], [4]. Similarly, users have to install a specific application in their smartphones to connect with the system. Besides that, once an individual is confirmed with the virus, that person can choose to allow health authorities to access the data in the app to help identify close contacts [5]. Moreover, a similar type of application is introduced by the Australian government namely “COVIDSafe”. In this case, also, a Bluetooth based contact tracing system is introduced with the feasibility to manually upload the contact data if a user becomes positive for COVID-19. However, with this development, they have not discussed the periodic changing of IDs of users but propose to store user data in an encrypted format to ensure privacy [6].

However, most of the above-mentioned developments have not discussed on real-time contact tracing and server-side algorithm implementations for the contact tracing functionalities. Moreover, they have not considered on continuous participation of the servers with the system and GPS tracking scenarios. We have identified that, even though the GPS based tracking systems can violate privacy policies, it is possible to obtain consent from the system users to share their location. Furthermore, GPS data will be highly useful for situations where high sensitive contact tracing and efficient isolation are required. Besides that, the available systems do not present any probability calculation for the exposed personals to be infected. Moreover, the available solutions are generating some common alerts considering the general parameters like the contact period and distance. However, we identified that the alerts should be specifically tailored for each user considering their current medical conditions and some chronic conditions which they are suffering for a while. In contrast, none of the above works has considered a tier-based detection. But that implementation is also important as the virus spreads in chains from one victim to another. Therefore, we are targeting the development of a more advanced system to mitigate the issues and drawbacks associated with the available solutions of COVID-19 contact tracing.

The TABLE I provides a detailed comparison between existing contact tracing systems for COVID-19 and our proposal. With this table, it is obvious that the proposing system provides a higher degree of uniqueness to the contact tracing.

TABLE I: Covid-19 Contact Tracing System Comparison

Characteristic	Ref [3]	Ref [4]	Ref [5]	Ref [6]	Our Prop:
Real-time data transmission & contact tracing	No	No	No	No	**Yes**
Hybrid location tracking in Bluetooth and GPS medium*	No	No	No	No	**Yes**
Anonymous periodically changing user identity	**Yes**	**Yes**	**Yes**	No	**Yes**
Bluetooth based contact-tracing	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Switchable manual and automatic data transmissions to servers**	No	No	No	No	**Yes**
Algorithm based infection probability prediction	No	Yes	No	No	**Yes**
Specifically tailored alerts for user	No	No	No	No	**Yes**
Tier-based contact tracing	No	No	No	No	**Yes**
*The GPS tracking is only functioning if the feature is enabled by the user. **User is given the full privilege on the data transmissions and he/she can select when the data to be transmitted.					

RSSI (Received Signal Strength Indicator) of BLE can be used to approximate the distance between two devices. RSSI depends on distance and broadcasting power [7]. To estimate the distance, a simplified form of the relation between distance and RSSI is widely used [8]. In [9], authors have provided a comprehensive guide to estimate distances using RSSI value in a BLE system. In this case, they propose a strategy to estimate the distances by changing the model of detection according to the RSSI value. We utilized the same strategy in our work as well.

III. Proposed Architecture

An overview of the proposed system architecture is shown in Fig. 1. As indicated from the architecture diagram, there are 3 major entities i.e., (i) users with smartphones, (ii) cloud servers and (iii) authorities and medical officers. To connect with the system, each user has to install a specific app in their smartphones and register with the system. Under the operation of the system, each smartphone broadcasts BLE advertisements as indications of its presence. In this case, the broadcasting advertisement will only consist of a random ID, which is assigned to the mobile phone via the cloud server during the registration. Especially this ID would change after a certain period to avoid unnecessary tracking of mobiles. The registered mobile phones continuously listen and make records of the advertisements receiving from the nearby mobiles. Here, the mobile app records two specific parameters, namely (i) RSSI value of the received BLE advertisements and (ii) contact period with each mobile. In addition to that, with the user permission, the mobile application keeps track of the GPS locations of the mobile relay periodically, according to user preferences. The mobile app is also capable of performing the initial risk level predictions associated with each contact, based on the above-mentioned personal parameters.

After gathering these data and calculating risk levels, the mobile will transmit the data into the cloud server via an active connection to perform second stage refined predictions and associated contact tracing. In this case, the data transmission work is performed as a real-time or periodic procedure according to the user preferences and the availability of the internet connection. Then, if one of the users get infected from COVID-19, the responsible authorities get access to server data and analyze to get more detailed outputs. In this case, specific algorithms aid with the server operation to extract out more accurate results. As a result of that, the medical officers can have a complete history of contacts up to 21 days which is the period the user data is kept, related to the specific patient. In addition to that, the servers can calculate the risk levels associated with each contact of the patient and predict their probability of infection. At the end of the procedure, the system notifies all the contacts according to their associate risk level and guide them to take further actions to avoid further spread of disease. Especially, the medical officers like doctors and public health inspectors who are working in regional areas related to the patient and his/her contacts can get notified to take immediate actions to neutralize the newly identified cluster. In addition to that, the authorities can get a map view of the traces of the patient if the GPS tracking feature is enabled by the user.

A. Calculation of contact distance using RSSI

Since the distance between two people is a very important factor, we have to approximate the proximity between two mobile users. Here, RSSI is the only measurement which can be obtained. Therefore we calculate the distance using the RSSI values of nearby advertising mobiles. We used a simplified form of the relation between distance and receive power as in [8], [10].

$$P_r(dBm) = P_{r1}(dBm) - K \cdot log_{10}(D(m)) \qquad (1)$$

where P_{r1} is the received power in dBm at 1 metre, K is the loss parameter and D is the distance between the receiver and the transmitter. In this case, we obtained values for K experimentally for an indoor environment. Here, the RSSI values and distances were recorded with a 1-metre interval for a range of 15 metres. RSSI readings were taken 30 times per each position in the range. The values of K are obtained to be in between 18 and 22 by applying the experimental average values to equation 1.

B. Infection Probability Prediction Algorithm

We also developed an algorithm to calculate the infection probability for a particular user in the system. For the algorithm, the probability of getting the infection from one person to another is assumed to be depending on two main factors: the distance and the contact period between them.

For the variation of probability of getting the infection with the distance, we assumed that,

$$P_d(x) = e^{-nx} \qquad (2)$$

where n is a positive constant and x is the distance. This distribution has the property of decreasing the probability of getting the infection with increasing distance between two users. For instance, the probability of getting the infection at a distance of 4 metres [11] is assumed to be 5% and the value of n is calculated accordingly.

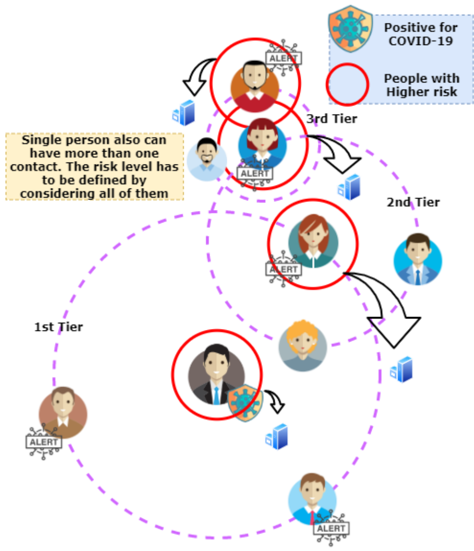


Fig. 2: Example Contact Tracing Process for a Single Sequence up to 3 Tiers

The variation of probability with the period of contact is taken as,

$$P_t(t) = 1 - e^{-mt} \tag{3}$$

where m is a positive constant and t is the period of contact. This probability distribution has the property of increasing the chances of getting the infection with more time. For instance, the 95% confidence of getting infected is taken as 10800 seconds (3 hours) [12] of the contact period in the simulations.

A simple illustration for a contact tracing in a single sequence provides in Fig. 2. As illustrated in Fig. 2, for a connection between two people a and b where a is in tier r and b is in the tier $r+1$, the contact distance d_{ab} and time t_{ab} of the connection between them are considered as independent and thus their probabilities are multiplied to get the probability of having b being infected by a. This probability is denoted by $P_i(b,a)$. Also, the total probability of getting the infection P_i to the person a affects the probability of getting the infection to b. These can be given as,

$$P_i(b,a) = P_i(a) \cdot P_d(d_{ab}) \cdot P_t(t_{ab}) \tag{4}$$

Apart from the distance and time, several other factors, such as user's medical conditions, can also be considered to calculate the score, if a user provides these personal details. If the contribution of a factor h to the probability is denoted as P_{c_h}, by considering k number of such factors, the probability $P_i(b,a)$ of person b getting infected by the person a, can be written as,

$$P_i(b,a) = min(P_i(a) \cdot P_d(d_{ab}) \cdot P_t(t_{ab}) + \sum_{h=1}^{k} P_{c_h}, 1) \tag{5}$$

In this case, to calculate the associated Risk Factors (RF), the case mortality rates presented in the [13] are used to derive the values for the P_{c_h}. Under this, three basic characteristics were considered as, age, comorbidity and gender. People who are suffering from some long term chronic diseases and people aged more than 60 years are highly vulnerable to epidemics due to their weak immunity. This fact also has proven by their higher death rates associated with COVID-19. Therefore in this algorithm, extra weight is added to the previously calculated probabilities (based on distance and contacted period) to generate more specific results to each user. Moreover, the base case scenarios for the risk factor calculation are available in TABLE II with an assignment of 0.01. Other than that, the RFs related to the other situations are calculated as relative variations of the base case scenario as indicated in TABLE II.

TABLE II: Base-Case Scenarios and Relative Risk Factors (RF) [13]

Age Group	RF	Comorbidity Condition	RF
0-9	0.010	Healthy (No-Comorbidity)	0.0100
10-19	0.010	Cancer (Any)	0.0622
20-29	0.010	Hypertension	0.0667
30-39	0.010	Chronic Respiratory Disease	0.0700
40-49	0.020	Diabetes	0.0811
50-59	0.065	Cardiovascular Disease	0.1167
60-69	0.180	**Gender Consideration**	**RF**
70-79	0.400	Female	0.0100
Age =>80	0.740	Male	0.0165

Since the person b can have q number of multiple connections from the previous tier, the total probability of getting the infection to b, $P_i(b)$, is taken as the minimum of either the sum of all probabilities from each connection or 1.

$$P_i(b) = min(\sum_{j=1}^{q} P_i(b,j), 1) \tag{6}$$

IV. Implementation

A BLE and location-based prototype mobile application is developed in our work as indicated in Fig. 3 to track user interactions and it is the pathway for users to connect with the system.

The mobile app was developed for Android mobiles using Android Studio 3.4. The app performs the user registrations and during the registration phase, the user's contact information such as mobile number, address, and email are recorded accordingly. Even though it is not mandatory, the users can optionally provide some of their health-related data (e.g. chronic conditions which they are suffering for a while) to receive more accurate and specifically tailored alerts regarding COVID-19. After successful registration, the user can log in and enable the automatic functioning mode. Then the app can run without any user intervention. Moreover, the users also have the privilege to enable or disable privacy features such as GPS tracking. The app enables the BLE advertising mode and BLE scanning mode operations and they will perform

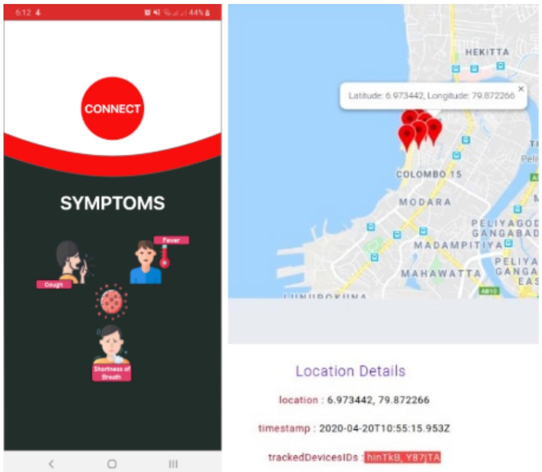


Fig. 3: Developed Mobile and Web Application Allows Users to Connect with the System and Administrators to Track User Locations

accordingly. The RSSI values of the nearby BLE advertising mobiles (will be converted into distance values), the user GPS location, and associated timestamps are recorded after each scan and stored in the app memory. In addition to that, the overall contact period with each of the nearby mobiles is also recorded as mentioned before. Once the internet is available, this data is sent to the cloud server via a web-socket. In this case, the user can select one of the three options to transmit the data on a real-time basis, transmit them periodically or manual transmission of the data according to his/her preferences. The server is implemented using the "Java Spring Boot framework". It consists of a set of Application Programming Interfaces (API) microservices. This model would help to scale-up the services when more user traffic is available.

A front-end web application is implemented using the Angular framework to view data of mobile users by authorized administrators. This web application consists of a login portal and upon successful login, the administrator can enter a phone number of any user and view the details of the location and nearby people within a particular period. The tracked locations are shown in a map along with nearby users' details for each pin on the map (Fig. 3). The administrator can also visualize these connections in a period using a graph to get more insights about the contacts. The graph consists of up to 3 tiers of information about direct and indirect contacts, as direct contacts can also have their contacts within the given period.

After tracing the contacts, alerts can be generated via emails and SMS message services. With these alerts, people with higher risks will be notified automatically, to be self quarantined and Polymerase Chain Reaction(PCR) tests can be performed based on the descending order of the risk. Regarding the privacy concerns, all the data will be gathered and transmitted with user consent and we have addressed the tracking protection with periodically changing random IDs.

V. Experiments and Results

To observe the effects and to verify the validity of the proposed algorithm, we simulated the system. For that, we used a graph-based approach to represent users as nodes and the connections among the users as edges. A node contains the probability of the user getting the infection and the user's personal details of chronic disease conditions, gender and age. The gender is initiated at random, which is equally distributed in the graph. A triangular distribution is approximated for the age such that the average age in the population is selected as the peak in the probability distribution. The chronic disease conditions are assumed to increase with age and set a maximum probability of two diseases per person with twice or more of the average age.

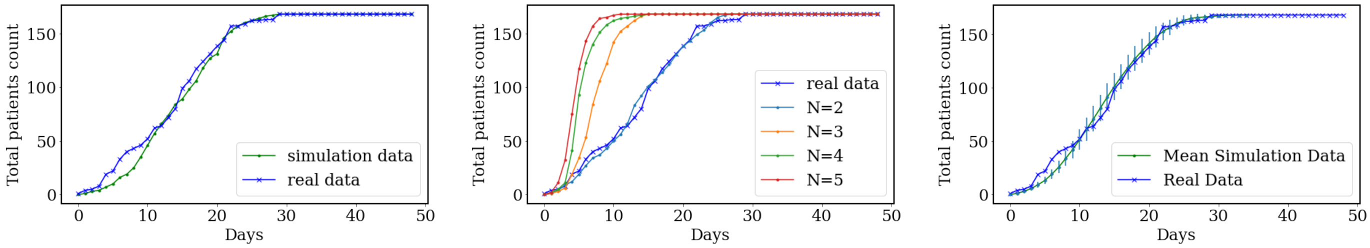
An edge consists of the duration of contact and the average distance between two nodes within the period. The formed graph is a representation of a certain duration, with connections among individuals.

Therefore, a graph is initialized with a fixed number of nodes and a set of edges randomly initialized from one node to other nodes. This random number is set to have a minimum of one edge and a maximum of $n-1$ where n is the total number of nodes in the graph. Each edge has distance and contact period values initiated at random. Initially, the probability of getting the infection in each node is set to zero. Then, a new patient is introduced to the graph by randomly selecting a node and all the other nodes update their probability based on our algorithm. This process is repeated for several iterations until all nodes become infected.

To compare our simulations with a real data set, we selected the COVID-19 patient infection data [14] from Hainan province in China. The starting date of the dataset is 22nd January 2020. A new patient was not identified from Hainan from 19th February 2020 to 7th May 2020 and the province had total confirmed cases of 168. Therefore, it is assumed that all the cases were identified in the province.

We created a graph with the same number of nodes as the 168 patients and simulated the addition of one new patient randomly with an iteration. One iteration is considered as one day of real data and plotted the total patient count from both simulated and real data. The simulation in Fig. 4a shows that the number of iterations is much less than the total number of nodes in the graph. That is due to the increments in the probability of getting the infection of healthy nodes. Over the iterations, some may get infected automatically. That resembles the real spread of the disease from one person to another.

The simulations in Fig. 4b shows that when the maximum number of edges is decreased, the number of iterations it takes to infect all the nodes is increased. According to this result, it verifies that self-isolation is important to avoid or slow down disease progression. Since the edges are created at random, we performed simulations of infecting all nodes for 100 iterations and obtained the mean patient count and the standard deviation per each day. This is shown in Fig. 4c.



(a) Comparison of Simulation and Real Data with Maximum Edges Count of 2

(b) Variation of Simulation Data with the Maximum Edges Count

(c) Comparison of Mean Data of 100 Simulations with the Real Data

Fig. 4: Graphs showing Comparison of Simulation Data with Real Patient Data of Hainan, China

Besides the above implementations, we also considered the power utilization of the mobile application. As the mobile application suppose to run as a background application continuously, high-level power efficiency is important. In this experiment, we tested with two android smartphones and the obtained results indicated as in TABLE III.

TABLE III: Mobile App Power Utilization

Mobile	Battery Capacity (mAh)	Total Memory (RAM)	App Run Time	Energy Consumption (mAh)	Energy Consumption as Battery Percentage(%)	Memory (RAM) Usage (MB)
Samsung A20	4000	3GB	1 hour	8	0.2	33
Samsung M20	5000	4GB	1 hour	10	0.2	36

From the obtained results it is clear that the application would run with lesser power consumption when it is running as a background service. In this case, we can expect power consumption of 192 - 240 mAh for a 24 hours operation of the application and it is only about 4.8% power consumption compared with the total battery capacity.

VI. Conclusion and Future Works

To address major issues described in contact tracing of COVID-19 patients, we have developed a contact tracing system with BLE and GPS capabilities while supporting both offline and online operation modes. On the other hand, we were able to analyze and generate infectious probabilities of users using the developed algorithm and finally, the algorithm enables to generate all the required alerts to indicate the important events and notify the users about their associated risk levels. Our work provides better options and flexibility over many proposed solutions and simulation results helped to obtain insights about how the system would function in a real scenario.

In the future, we plan to improve privacy while collecting the data by adding strong anonymity and unlinkability properties. Moreover, we are planning to integrate machine learning-based probability predictions to further improve the accuracy of prediction results.

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