Users' Expectations, Experiences, and Concerns With COVID Alert, an Exposure-Notification App

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We conducted semi-structured interviews with 20 users of Canada's exposure-notification app, COVID Alert. We identified several types of users' mental models for the app. Participants' concerns were found to correlate with their level of understanding of the app. Compared to a centralized contact-tracing app, COVID Alert was favored for its more efficient notification delivery method, its higher privacy protection, and its optional level of cooperation. Based on our findings, we suggest decision-makers rethink the app's privacy-utility trade-off and improve its utility by giving users more control over their data. We also suggest technology companies build and maintain trust with the public. Further, we recommend increasing diagnosed users' motivation to notify the app and encouraging exposed users to follow the guidelines. Last, we provide design suggestions to help users with *Unsound* and *Innocent* mental models to better understand the app.

CCS Concepts: • **Human-centered computing** → **Empirical studies in HCI**; *Human computer interaction (HCI)*; **Empirical studies in HCI**; **Empirical studies in HCI**; • **Security and privacy** → *Human and societal aspects of security and privacy*; Usability in security and privacy; **Usability in security and privacy**;

Additional Key Words and Phrases: user study, COVID-19 exposure-notification apps, mental models, privacy concerns

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1 INTRODUCTION

Numerous smartphone apps have been implemented worldwide to help with contact tracing during the COVID-19 pandemic. According to the data compiled by Top10VPN.com [199], 120 contact-tracing apps have been launched worldwide in 71 countries and regions. For instance, the Singaporean government launched TraceTogether, which employs Bluetooth to track users' proximity to other users. It alerts those who come in close contact with someone who has tested positive for COVID-19 or is at high risk of carrying the coronavirus [193].

The effectiveness of contact-tracing apps depends on various factors, including the adoption rate, positive-case reporting rate, and long-term usage of the app [54, 74, 139]. For instance, according

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to a study conducted by Oxford epidemiologists [54], an adoption rate of approximately 60% of the total population is necessary for contact-tracing apps to be effective. However, in countries where contact tracing has been voluntary during the pandemic, the app adoption rate remained low (from 42% adoption in New Zealand to 0.77% in Cyprus) [40].

Previous contact-tracing app studies focused on identifying the privacy and security risks associated with these kinds of apps. Many risks were discovered regarding different apps' data practices [12, 194, 199], such as massive collection of users' data [12]. Furthermore, many studies investigated public attitudes toward contact-tracing apps [34, 105, 109, 141, 146, 169, 187, 197]. Specifically, a variety of factors have been identified that could influence the public's willingness to adopt contact-tracing apps. The factors include privacy considerations, accuracy concerns, perceived benefits, perceived barriers, individual differences, and the data architecture of the app [2, 3, 7, 14, 70, 75, 89, 91, 100, 152, 161, 177, 186, 189, 190, 204].

However, real users' experiences of contact-tracing apps have received little research attention. With the continuing spread of novel coronavirus worldwide and the low reporting rate of positive cases through contact-tracing apps in many regions and countries [45, 73, 164, 179], users' experiences need to be understood. An exploration of users' desire for exposure notification and their concerns, challenges, and mental models of the app could help researchers discover underlying issues in the current design of such apps, and users' possible misconceptions, and unmet expectations. The research results could inform the new design of contact-tracing apps to better support users' needs and help users contribute to controlling the pandemic. We, therefore, conducted an exploratory study to learn about users' experiences.

We conducted our investigation through semi-structured interviews with 20 users of the COVID Alert app. Our interviews focused on users' motivations and expectations for learning about their exposure to COVID-19, users' mental models of the app, and users' concerns about COVID Alert.

We base our research on COVID Alert app. Based on the privacy-preserving contact-tracing API developed by Apple and Google [64], the COVID Alert app is the Canadian government's exposure-notification app[1] to facilitate digital contact tracing [64, 125].

Our results suggest that if users have been in close contact with a COVID-positive person, they expect more information than what is provided by COVID Alert (e.g., the time and place of the exposure). Furthermore, we discovered participants had various mental models of the app. Their concerns were associated with their understanding of certain aspects of the app. Specifically, participants with *Unsound* mental models expressed privacy concerns due to misunderstandings and distrust. Meanwhile, other identified user concerns were correlated with their correct understanding of the app. In addition, our results show participants did not have a united preference toward a centralized or decentralized design of exposure-notification apps. Compared to a centralized proximity-based exposure-notification app, COVID Alert was favored for its higher level of privacy protection, option to cooperate, and more efficient notification delivery method.

Based on our findings, we suggest decision-makers rethink the app's privacy-utility trade-off and give users more control over their data. Moreover, we recommend increasing diagnosed COVID-positive users' motivation to notify the app and encouraging exposed users to follow the guidelines. More detailed guidelines may motivate users to follow them. Further, we suggest technology companies build and maintain trust with the public. Finally, we make design suggestions to improve users' mental models.

[1]There is no commonly shared agreement on the differences between contact-tracing apps and exposure-notification apps. Exposure-notification apps are often referred to as *contact-tracing apps* [26, 43, 145]. We define exposure-notification apps as those designed to warn users of contact with an infected individual without allowing the public health authorities to identify the users.

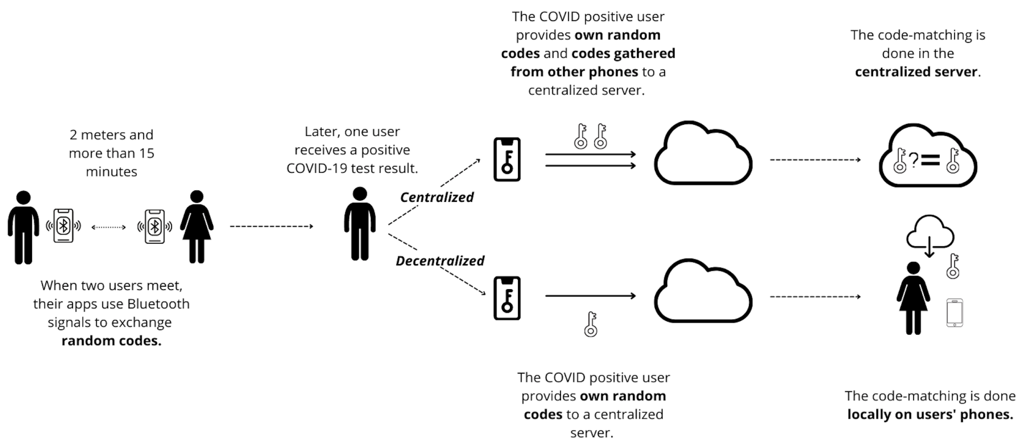

Fig. 1. Bluetooth-based proximity contact tracing with centralized and decentralized architecture

Our contributions include the first *qualitative* study (to the best of our knowledge) to investigate users' experiences with an exposure-notification app. This study focused on exploring users' understanding of the app, their concerns about it, and their unfulfilled needs regarding it. Based on the findings, we offer practical design recommendations that could be useful in the development of digital tracing tools. We believe these recommendations could lead to better support of users' needs and better protection of communities' health.

2 BACKGROUND AND RELATED WORK

In this section, we first provide a background on proximity-based contact-tracing apps and explain the design and features of the COVID Alert app. Then we summarize the literature on the risks associated with contact-tracing apps and on public opinions about them. We also summarize the studies about users' mental models. We conclude by discussing the differences between our research and previous studies.

2.1 Centralized and Decentralized Proximity-Based Contact-Tracing Apps

For the purpose of this paper, we distinguish between proximity-based (which utilize Bluetooth) and location-based contact-tracing apps. COVID Alert and others are proximity-based, using Bluetooth to exchange proximity identifiers with nearby phones. A *proximity identifier* is a random code generated by an app and exchanged with phones via Bluetooth. Such apps use the strength of the Bluetooth signal to estimate the distance between users' smartphones. The heuristics of these apps determine a COVID-19 exposure event has taken place if two smartphones are (1) in close proximity (usually 2 m) (2) for a predetermined period of time (usually 15 minutes) or longer. In this paper, we discuss only those exposure-detection and -notification apps that use Bluetooth-based proximity detection.

We further categorize these selected apps as centralized or decentralized. As illustrated in Figure 1, apps based on a centralized architecture upload random codes and codes gathered from other phones to a central server (usually administered by or on behalf of a public health authority). The central server detects exposure to COVID-19 infected users (referred to as *C-positive users* in this paper). Users of centralized apps are usually asked to provide contact information (e.g., their phone number) so health authorities can notify them about exposure to a C-positive user.

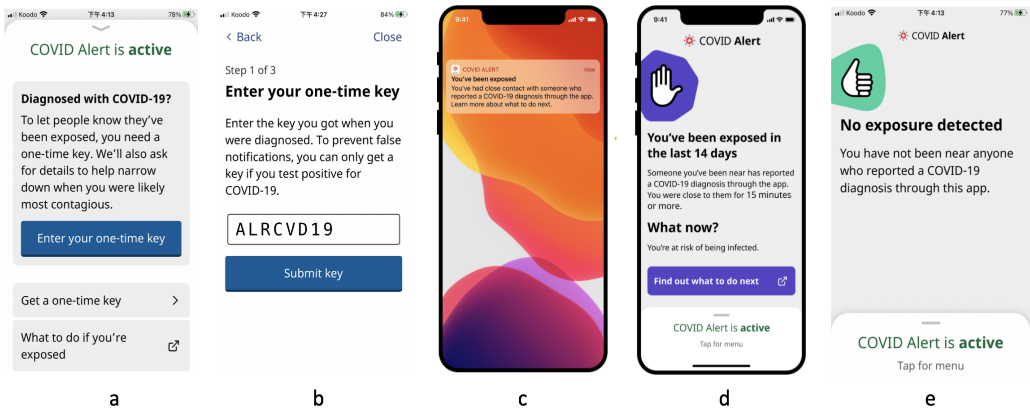

Fig. 2. Screenshots of instructions for exposed users' one-time code to COVID Alert (a and b), of the notification and instructions for exposed users (c and d) [132], and of the message unexposed users see (e)

Examples of centralized proximity-based contact-tracing apps include TraceTogether, careFIJI, and TousAntiCovid. TraceTogether is used in Singapore [193] with an estimated adoption rate of 40% [40], careFIJI in Fiji [136] with an estimated adoption rate of 8% [40], and TousAntiCovid in France [57] with an estimated adoption rate of 7.5% [40]. ABTraceTogether is another centralized contact-tracing app but only available in the province of Alberta in Canada [135]. It was the first government app launched in Canada (available in May 2020) and has an estimated adoption rate of less than 1% [51].

In a decentralized architecture, each app locally determines if its user has been exposed to C-positive users. For this to happen, C-positive users must instruct their app to upload locally generated proximity identifiers to the central server. When the server receives a set of proximity identifiers from the app of a C-positive user, it makes these identifiers available for download to all other users. By comparing C-positive users' identifiers (downloaded from the server) with those received via Bluetooth, exposure to C-positive users is determined in a decentralized way on each user's phone. Canada's COVID Alert is one such decentralized app that utilizes Bluetooth-based proximity detection. Besides COVID Alert, more than 60 other apps also use a decentralized data structure [64, 149], such as Stopp Corona, Corona-Warn-App, and COVID Tracker. Stopp Corona is used in Australia [208] with an estimated adoption rate between 25% and 35% [32], Corona-Warn-App in Germany [196] with an estimated adoption rate of 29.1% [40], and COVID Tracker in Ireland [77] with an estimated adoption rate of 35% [40].

2.2 COVID Alert

COVID Alert is Canada's exposure-notification app to help limit the spread of COVID-19. It is developed based on the privacy-preserving contact-tracing API developed by Apple and Google [64]. COVID Alert was first announced on June 18, 2020, and launched on July 31, 2020 [173]. As of January 2021, COVID Alert was available for Canadians in 9 out of 13 provinces and territories. As of October 25, 2021, the app had been downloaded over six million times, which represents approximately 20% of smartphone users in Canada [122, 171]. Since the app first launched, more than 36,000 people had used the app to notify others after becoming C-positive [122, 126].

COVID Alert provides three main features, i.e., three tasks users can perform on the app [122, 126]. First, the app allows C-positive users to voluntarily notify other users in a decentralized manner.

If an app user tests positive for the virus, their local health authorities will give them a one-time key [125]. The C-positive user then has the option to use this key to upload their random codes (see Figures 2a and 2b) to a central server located in Canada. In addition, the C-positive user has the option to enter the date of their symptom onset or test. The app uses this information to determine what dates they were likely to have been the most infectious. As a result, only users who were near the C-positive user during that time will be notified. If the C-positive user does not enter their date of symptom onset or test, all users who were near the C-positive user in the last 14 days will be notified [127]. Meanwhile on other users' phones, COVID Alert continues to download the random codes from app users who have reported a C-positive diagnosis. If there is a match between the downloaded random codes and those received via Bluetooth, the user will automatically receive a notification indicating they have been exposed (referred to in this paper as an *exposed user*) and the next steps to take (see Figures 2c and 2d). Hence, receiving an exposure notification does not require users to perform any specific task. If a user does not receive an exposure notification, the app will indicate no exposure has been detected (see Figure 2e). Second, COVID Alert allows users to clear the screen indicating their exposure to COVID-19, once they have received a negative COVID-19 test result. This feature enables the app to alert the user with a new exposure. Third, users can turn COVID Alert off without disabling Bluetooth.

2.3 Security and Privacy Risks of Contact-Tracing Apps

By analyzing contact-tracing apps, researchers have identified many of the privacy and security risks associated with them. These risks include collecting users' personal information [12, 52, 71, 90], having no stated anonymity policies or hard-to-understand ones [199, 205], asking for unnecessary data-accessing permissions [13], and possibly exposing users' identifiable information [194].

Casagrande et al. [29] analyzed eight popular contact-tracing apps (e.g., SwissCovid [134]) and found all of them vulnerable to relay attacks. Cho et al. [33] analyzed Singapore's TraceTogether app [193] and identified three aspects of privacy potentially compromised by the app: privacy from snoopers, from contacts, and from the authorities. Further, researchers analyzed the pros and cons of three common tracing-app architectures, i.e., centralized, decentralized, and hybrid. Both groups concluded no current technological solution can provide privacy guarantees, effectiveness, and freedom from cyberattacks [4, 96].

2.4 Public Opinion about Contact-Tracing Apps

A number of studies have examined public acceptance of different types of contact-tracing apps. Specifically, studies have been done to measure public intentions of adopting contact-tracing apps [7, 22, 34, 109, 114, 146, 148, 175, 177]. Further, researchers have identified factors that could influence users' willingness to adopt contact-tracing apps, including perceived benefits [20, 65, 89, 112, 152, 188, 189, 198], solution accuracy [89, 143, 152], privacy considerations (e.g., government surveillance) [2, 3, 7, 31, 75, 89, 100, 142, 152, 197, 204, 207], security concerns [2, 98], efficacy concerns [8, 47, 75, 110, 148, 185, 188, 189], usability [18, 143], perceived stigma [82, 197], personal health conditions [68, 114], trust of the government [7, 65, 68, 80, 158, 207], technical malfunctions [180], and mobile-related costs [19, 75, 152]. Additionally, the influence of different factors on the public's adoption intentions has been studied [89, 177]. The results show 75%–80% of people would consider installing a private and accurate app [89].

2.5 Studies of Users' Mental Models

The exploration of mental models helps researchers better understand users' reasoning about a system [119]. Mental models are widely accepted as the internal representations people develop to understand and operate a system [24, 35, 69, 83, 118]. Users' mental models of a system can be incomplete, unstable, unscientific, parsimonious, and misconceived [117, 201]. Previous work suggests that users' mental models are associated with their concerns [87, 107, 202], behaviors [37], and app performance [155]. Based on different aspects, users' mental models can be categorized into various types [28, 151, 160, 201]. There are two main categories of users' mental models [93, 160]: functional (similar to a task/action model in [201]) and structural (similar to a surrogate model in [201]). Functional models imply that users only acknowledge information about a selected set of functions so they can perform a specific task, whereas structural models indicate that users have a deep and detailed understanding of how and why a system works [46, 93, 117, 206]. This dual grouping of mental models is acknowledged by Nielsen [116] and has been confirmed by several studies [78, 93, 104].

Our study differs from previous studies in three ways. First, instead of presenting the participants with a hypothetical situation, we investigated real users' experiences with an exposure-notification app. An exploration of the participants' experiences and unmet expectations can help researchers discover the underlying issues with the current design of exposure-notification apps, thereby informing the future design of such tools. Second, compared to several qualitative studies [22, 65, 197], our qualitative approach focuses on investigating users' understanding of the app, their concerns about it, and their unmet needs regarding it. Third, compared to many previous quantitative studies, our qualitative approach helped us understand the *reasoning* for participants' expectations and concerns, and the linkage between their understanding of the app and their concerns. Our findings can provide insights for future designs of similar tracing tools.

3 METHOD

We advertised on social media and conducted the interviews using video conferencing. A variety of platforms were used to recruit participants in Canada, including Facebook, Twitter, Reddit, Kijiji, and our institution's paid-participant study list. The interviews were performed between August 12, 2020, and January 4, 2021. We used a screening survey to select a diverse sample of participants in terms of age, occupation, and education level. Due to the COVID-19 pandemic, participants were interviewed using video calls. Each participant was compensated with $25 CAD, either via an electronic transfer or an Amazon.ca gift card. The average duration of an interview was 56 minutes. This study was approved by our institution's research ethics board.

3.1 Data Collection

General questions: Participants were asked to describe their experience of living during the COVID-19 pandemic, the challenges they were experiencing, and the resources they were using to obtain information about the pandemic.

Motivations and expectations for learning of exposure to COVID-19: The participants were asked to describe the COVID-19 exposure scenarios they wanted to be notified of and the reasons they wanted those notifications. If a participant had such a scenario, we further explored what information they wished to obtain. For example, we asked, *"Since you want to be notified, what information do you want to learn?"*

Mental models of COVID Alert: We used a combination of a drawing exercise and a verbal explanation to obtain participants' perceptions of the COVID Alert app. Drawing has been widely used as a complementary approach to verbal explanation to best capture users' mental models [58, 78, 84, 86, 150, 202]. To avoid introducing ideas into their heads, we first asked the participants to perform a drawing task to explain how they think COVID Alert works. The interviewing researchers told them to take as long as they wanted to draw. After the drawing task was completed, the participants were guided to take a picture of their drawing and send it to the interviewing researchers via email. The participants were then asked to verbally explain their thinking process with reference to their drawings. If there was any confusion on the researcher's part, follow-up questions were asked. For example, if the researcher noticed symbols on the drawing that were not initially explained by the participant, the researcher asked, *"What does this symbol stand for?"*

Concerns about COVID Alert and corresponding coping strategies: When exploring participants' concerns, we avoided bringing up any specific threats so we could get unbiased responses. Instead, we asked more general questions to elicit participants' concerns without explicitly mentioning them. For instance, we asked participants if they had experienced any challenges using the app. We also explored participants' concerns based on their mental models of the app. For instance, if a participant believed their location information was collected by the app, we further explored their perception of such data collection. We also made it clear that a lack of concern was a valid response. When a concern was expressed by a participant, we further explored the coping strategies (if any) they used to address that concern. Later, through screen sharing we presented a description of a centralized contact-tracing app.[2]). The description explained in detail how a centralized contact-tracing app works, such as its use of Bluetooth signals to identify nearby phones. This description was based on existing centralized proximity-based apps, such as ABTrace Together [5], TraceTogether [193], and COVIDSafe [130]. The participant was asked to compare the presented centralized app with the COVID Alert app. If the participant voiced a preference, they were asked to further explain their preference.

Wrap-up: Finally, we asked the participants if they wanted to provide any other information they considered relevant to the study.

3.2 Data Analysis

We used a qualitative and iterative coding process based on a grounded theory approach [38, 61, 106]. We conducted five pilot interviews to test our data collection [162]. All researchers discussed the findings from the pilot interviews and added a new question to the interview guide. This question was solicited from participants' exposure scenarios they wanted to be notified of. Specifically, we found that participants identified other scenarios they wanted to be notified of, besides the close-contact one (e.g., shop-in-the-same-supermarket scenario in pilot 5). Our adjustment of the interview guide allowed us to explore participants' expectations and reasoning of an exposure scenario without limiting them within the scope of COVID Alert. Meanwhile, as with most semi-structured interviews [181], we sometimes asked follow-up questions to elicit additional information about participants' reasoning. Data from the pilots was not included in the analysis.

As explained in §3.1, in order to investigate participants' mental models of the app, participants were asked to conduct a drawing task and use it as supplementary material to help explain their understanding of the app. Participants' verbal explanations were audio recorded and transcribed with the rest of their interview. When analyzing participants' mental models, researchers examined their verbal explanations while referring to their drawings to capture a complete picture of participants' understanding.

Similar to many qualitative studies using grounded theory [1, 25, 81, 154, 192], we performed open, axial, and selective coding to analyze the data. Two researchers independently performed open coding using the NVivo tool [120]. A total of 204 codes were identified through open coding. During axial coding, two coauthors grouped the codes into six categories. Subsequently, all the coauthors worked together to select the core category and relate it to the other categories [38].

[2]see the description at https://github.com/AUXResearcher/CSCW2022/blob/main/CSCW.pdf.

Table 1. Summary of participants' demographics

P#	Age	Gender	Occupation	Education level
1	33	F	Communications advisor	Bachelor
2	55	F	Human resources director	Bachelor
3	54	M	Executive director	Master
4	39	F	News editor	Community college
5	28	F	Actress	Community college
6	29	F	Accountant	Bachelor
7	39	M	Customer service representative	High school
8	57	M	COVID compliance officer	Bachelor
9	26	M	Project associate	Master
10	62	F	Retired	Bachelor
11	66	F	Retired	Bachelor
12	19	M	Full-time university student and part-time event planner	High school
13	36	M	English tutor	Bachelor
14	32	M	Administrative assistant	High school
15	50	F	Nurse	Bachelor
16	30	F	Unemployed	High school
17	57	M	Chief financial officer	Master
18	30	M	Technical support	Bachelor
19	45	M	Environmental analyst	Bachelor
20	40	M	Project manager	Bachelor

Theoretical saturation was reached after 18 participants were interviewed [42, 62]. We further conducted two more interviews to confirm that no new codes would appear.[3]

4 RESULTS

4.1 Participants

We carried out semi-structured interviews with 20 participants. Their ages ranged from 19 to 66 years (average 42, median 40). Eleven of them were female. COVID Alert was the only contact-tracing app our participants were using when they were interviewed. Participants kept the app running in the background most of the time. Two of them had received an exposure notification from the app, and none of them had used the app to notify others. Participants' demographics are summarized in Table 1.

4.2 Motivations and Expectations for Learning of Exposure to COVID-19

Our research is based on the use of COVID Alert, an exposure-notification app that informs users of close contact with a C-positive person. Hence, this paper reports only on participants' motivations and expectations for the close-contact exposure scenario.

We explored the exposure scenarios participants wanted to be informed of. Since one of the main functions of contact-tracing apps is to alert users when they have been in close contact with C-positive people, we sought to understand participants' motivations and expectations for learning about their exposure to COVID-19. This exploration allowed us to better understand participants' expectations of exposure notifications and to explore their unfulfilled needs (if any) without limiting them within the scope of a contact-tracing app.

Overall, participants identified three exposure scenarios they wanted to be informed of. First, participants wanted to be informed if they lived in the same neighborhood as a C-positive person (e.g., shopping at the same market), even if they had not been directly exposed, i.e., less than 2 meters for at least 15 minutes. The second scenario was living in the same building with a C-positive person (e.g., sharing the same laundry room, door handles, and elevator buttons). In this scenario, participants believed they risked infection even without direct interactions with the

[3] see the saturation graph at https://github.com/AUXResearcher/CSCW2022/blob/main/CSCW.pdf.

C-positive person because they thought the COVID-19 virus could be spread through contaminated surfaces, i.e., fomites [63]. Compared with the first scenario, participants believed the second scenario increased their chances of infection and was more important for them to be notified about. The third scenario was being in close contact, i.e., less than 2 meters for at least 15 minutes, with a C-positive person. We further explored participants' expectations and their reasoning in this scenario, without limiting them within the scope of the COVID Alert app.

Participants brought up several examples of being in close contact with a C-positive person, including being on the same plane, being on the same bus, and sharing a workplace. In this exposure scenario, participants wanted to learn about the time and place of the exposure, to understand the severity of patients' symptoms, to obtain detailed behavior guidelines, and to know the identity of C-positive people. We further explored participants' reasons for having such preferences.

Time and place of the exposure: Simply knowing they have been exposed was not enough for participants. They wanted to be informed about the time and location of the exposure, so they could conduct their own contact tracing and estimate their probability of being infected. For example, P3 believed this knowledge could help him estimate the risk of infection and take actions accordingly: *"... is it just one interaction and [the C-positive person] was just around for a few minutes? Is it somebody who sits across from you for three hours? So, [having] those pieces of information like when and where [the interaction happened], I think I will be able to make my own decisions and form my own opinion as to what should I do next."*

Severity of patients' symptoms: A few participants wanted to know about patients' conditions. Acting on the assumption that patients with severe symptoms would be more contagious, participants hoped this information would help them estimate their own risks of infection. For example, P16 noted: *"If [the C-positive person] has very severe symptoms, it makes me think that maybe they are more transmissible. I would want to know if they are hospitalized or not. Then I will know if I am at high risk or not."*

Behavior guidelines: Some participants wanted to receive detailed guidelines from authorities. They expected such guidelines to include instructions for the exposed person to protect others who may also be at risk. Participants also wanted to obtain information regarding their own health status. Examples of this information included their likelihood of being infected in particular situations, when and what symptoms might arise, and the feasibility of being tested. For example, P18 remarked: *"I would like to know how likely [it is that] I am in danger, then what should I do next."*

C-positive people's identitities: Some participants wanted to learn the identities of diagnosed people, so they could be more informed, adjust their future behaviors, and/or provide moral support.

A couple of participants indicated curiosity and the desire for more information as their reasons for wanting to learn C-positive people's identities. To illustrate, P13 remarked: *"I think it is just wanting more information, even if it may not be rationally helpful. Like, it would be interesting to know that person [who] tested positive."* A few participants wanted to know the identities of C-positive people, so they could adjust their future behaviors, such as avoiding social gatherings. To illustrate, P6 stated: *"Because [the identity of the C-positive person] can help to determine what group of people they are in. Are they in my friend group or my colleague group? You know, to understand, in the future do we have to avoid any [type of gathering]?"* Meanwhile, other participants wanted to provide help or moral support to the infected, especially if they had a personal relationship with them. To illustrate, P14 explained: *"If [the C-positive person] is my roommate, then I definitely want to know ... I can call the ambulance if he needs me to [or] at least provide some moral support."*

Participants expressed different attitudes for disclosing their own identities if diagnosed with COVID-19. After participants expressed a desire to learn the identities of C-positive people, we further explored their willingness to disclose their own identities if they tested positive. Interestingly, a couple of these participants would refuse to disclose their own identities in such scenarios, citing concerns about stigma and privacy. To illustrate, P13 stated: *"I am not sure that I would want people to know that I have it, in case there is, like, a stigma."* Meanwhile, other participants indicated their identities should be shared only under certain circumstances, such as with family members or with people they had close contact with. For example, P7 believed his identity should only be disclosed to people he had close contact with and for the purpose of protecting their health: *"I would not want my name posted on the Internet. But if people may have interacted with me, then [they] should be notified ... but in strictly controlled circumstances where it is necessary for their health, like get them tested."* One participant (P3) was comfortable with sharing his identity: *"Well, I mean, it is a little invasive, certainly. But if we are dealing with a major outbreak, then I do not care about the privacy issue."*

4.3 Mental Models of COVID Alert

Participants' mental models of COVID Alert were categorized into *Innocent*, *Unsound*, *Structural*, and *Advanced*. Building on previous literature [60, 78, 200, 203], we classified the mental models based on the differences in participants' understandings of the app's aspects. These aspects were derived from our interview data, which was collected from a diverse sample of participants. By analyzing participants' verbal descriptions with reference to their drawings, we pinpointed eight aspects of the app (see details in Table 2). For instance, participants with *Unsound*[4] mental models had an incorrect understanding of whether users' location data is collected or not. This is probably why most of them incorrectly understood how exposed users are identified. In the rest of this section, we describe the identified mental models and the differences among them.

4.3.1 Innocent *Mental Model.* Participants with an *Innocent* mental model knew little about COVID Alert. Regarding the app's function of receiving exposure notifications and its use of Bluetooth technology, *Innocent* understanding was more limited than *Structural* and *Advanced* yet more accurate than *Unsound*, as Table 2 illustrates. However, they were uncertain about other aspects of the app.

The well-known functional model in previous literature indicates that users will know how to make use of a system's functionality to perform a specific task but will not know how the system works in detail [46, 93, 206]. Our participants with an *Innocent* mental model did not know how the app works in detail. But they also did not know how to perform any task available in the app, such as notifying other users about testing positive (check §2.2 for the tasks users can perform on the app). They did, however, know the app automatically notifies them if they are exposed (see Table 2). As these participants had very little knowledge of the app (even compared to the users with functional models defined in the literature), we categorized their mental model as *Innocent*.

To illustrate, when P13 explained how the app works (using his drawing, shown in Figure 3), he drew and described only that the app uses Bluetooth signals to identify nearby phones and notify users at risk of exposure. He was unclear about how the app determines exposure and how C-positive users notify others, even after he was directly prompted. When we explored the reasons for this type of gap, we found that *Innocent* participants trusted the government and the app designers. Hence, they lacked motivation to learn more about the app. For example, P13 said: *"I did not research on the app; I just trust the experts to figure out all the details."*

[4]We borrowed the label for this mental model from [93].

Table 2. Participants' mental models of COVID Alert actions and processes
Legend: "✓" means the participant's mental model includes this specific aspect, and their understanding of it is sound. "×" means the participant misunderstands one or more parts of this specific aspect. "◯" means the participant did not know or was uncertain of the app's action or process in this specific aspect.

Mental model	P#	Receive an exposure notification	Notify others after diagnosed with COVID-19	How is exposure to C-positive users determined? (Bluetooth signal to exchange random codes with nearby phones)	What constitutes a close contact? (less than 2 m and at least for 15 minutes)	How can C-positive users inform others? (Voluntarily use a one-time key to upload their random codes to central server.)	How can users know if they have been exposed? (Users' phones keep downloading random codes from central server and comparing them with collected ones. If a match, app notifies its user.)	What information/guidelines are provided to exposed users? (Recommended to take a test first and wait for results while staying at home. If tested positive, recommended to self-isolate and notify others through the app. If tested negative, recommended to monitor themselves.)	Location and time are collected or used
Innocent	P12	✓	◯	✓	◯	◯	◯	◯	✓
Innocent	P13	✓	◯	✓	◯	◯	◯	◯	✓
Unsound	P2	✓	✓	×	◯	◯	◯	◯	×
Unsound	P5	✓	✓	×	◯	◯	◯	◯	×
Unsound	P14	×	◯	×	◯	◯	◯	◯	×
Unsound	P16	✓	✓	×	✓	✓	◯	✓	×
Unsound	P18	×	◯	×	◯	◯	◯	◯	×
Unsound	P20	✓	✓	×	✓	✓	◯	×	×
Unsound	P8	✓	✓	✓	✓	✓	◯	✓	×
Unsound	P17	✓	✓	✓	✓	✓	◯	×	×
Structural	P1	✓	✓	✓	✓	✓	◯	◯	✓
Structural	P4	✓	✓	✓	✓	✓	◯	◯	✓
Structural	P6	✓	✓	✓	✓	✓	◯	✓	✓
Structural	P7	✓	✓	✓	✓	✓	◯	✓	✓
Structural	P9	✓	✓	✓	✓	✓	◯	✓	✓
Structural	P10	✓	✓	✓	✓	✓	◯	◯	✓
Structural	P11	✓	✓	✓	✓	✓	◯	✓	✓
Structural	P15	✓	✓	✓	✓	✓	◯	✓	✓
Structural	P19	✓	✓	✓	✓	✓	◯	✓	✓
Advanced	P3	✓	✓	✓	✓	✓	✓	✓	✓

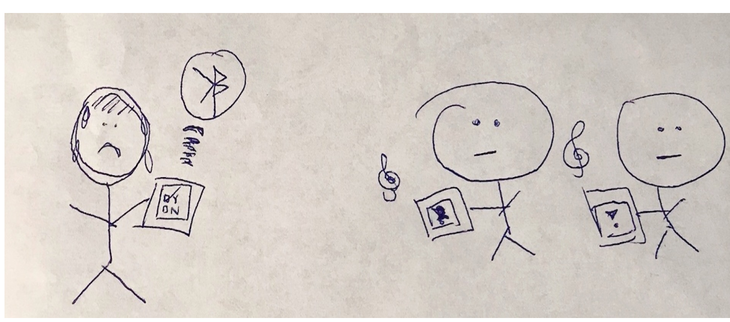

Fig. 3. A drawing by P13 illustrates an *Innocent* mental model. The drawing shows Bluetooth signals are used to identify nearby phones, and users will receive a notification if at risk of exposure.

4.3.2 Unsound *Mental Model.* Compared to other participants, those with an *Unsound* mental model (N = 8) had several important misconceptions. Most participants in this group believed the app decides they are exposed to a C-positive user if they are at the same location at the same time as that user. To illustrate, P5 remarked: *"The app collects, like, GPS data. When a person reports being infected, [the app] then matches all the location data, and you will get an alert saying that you have crossed paths with somebody with COVID."* Another example is P20. He believed the app not only works with Google Maps (see Figure 4 for his drawing) but the exposure notification would also indicate when and where the exposure happened: *" ... [the COVID Alert app] will show where you have crossed paths with that [C-positive] individual."* P18 and P14 had another important misconception, believing the app informs them in real time when a C-positive user is nearby. To illustrate, P18 stated: *"I think [the app] can show there is a person who has been tested positive in front of you. For example, five meters away from you."*

By taking the position that the user is always right [113], we carefully explored how these participants developed an *Unsound* mental model. One possible reason could be they missed appropriate

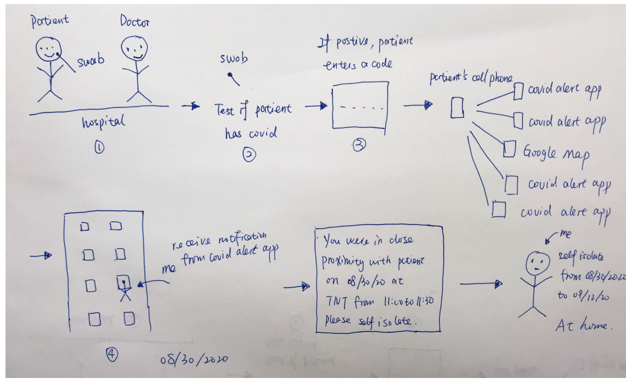

Fig. 4. A drawing by P20 illustrates an *Unsound* mental model. P20 explained that after C-positive users enter a code to the COVID Alert app, Google Maps is granted permission to access their locations for the last two weeks. The location data is then used to identify exposed users.

descriptions for the app [157]. For instance, a couple of the participants did not remember obtaining any description for the app and indicated they *"skimmed through some information online"* (P2) and *"read a couple of news articles"* (P5).

Two other participants (P8 and P17) were aware the app used Bluetooth to identify nearby phones. However, they nevertheless misunderstood that the app collects their location data. For instance, when discussing what information users would receive when notified of exposure, P17 stated: *"Location and time [of the exposure], like I was at the [supermarket name] on this corner on Wednesday from two until four. [Like] I was [exposed] at my work on Monday from nine to five. I think [the app] collects that information. I do not think that [the app] says it does, but I think it does."*

4.3.3 Structural *Mental Model.* Participants with a *Structural* mental model ($N = 9$) had a correct and relatively complete understanding of what the app does and how it does it. They knew the app uses Bluetooth signals rather than GPS to identify phones in close proximity (2 meters) and time (15 minutes) to decide if exposure occurred. Moreover, these participants were able to describe that C-positive users could enter a one-time key into the app to send exposure notifications to others. Some of them were also aware of the information provided on the exposure notification and the guidelines provided to exposed users (through research and/or the exposure notification they previously received). For example, P9 accurately drew (see Figure 5) and explained that a C-positive user can enter a one-time key to let the app inform those at risk of exposure.

However, there were gaps in these participants' mental model, specifically when compared with the *Advanced* one (see details in Table 2). These participants were unaware that the app continuously downloads random codes from the central server or that the code-matching process is conducted locally on their phones (not on the server). For instance, P7 explained: *"The system will automatically alert users who have been in close contact with the patient."* However, he was *"not quite sure"* how the system identifies exposed users.

4.3.4 Advanced *Mental Model.* One participant (P3) had the most complete and highest technical understanding of the COVID Alert app. When compared with all other participants, he was able to explain that the contact-matching process is conducted in a decentralized way (see details in Table 2). While describing how users are notified, he stated: *"You have to connect your phone with the Internet. Then your phone will constantly download the data [about C-positive users]. All your*

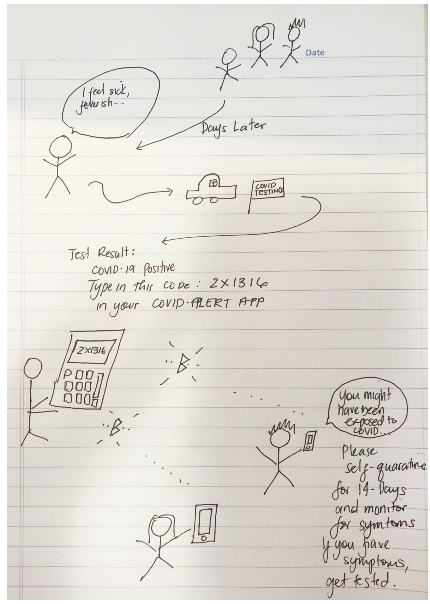

Fig. 5. A drawing by P9 illustrates a *Structural* mental model. The drawing shows that users can send and receive exposure notifications, the Bluetooth signal is used to determine a "close contact," and C-positive users have an option to notify others (left bottom of the drawing). Further, the drawing indicates exposed users will get a notification with detailed guidelines (right bottom of the drawing).

data is stored on your phone, like, [it] does not go anywhere. So, basically, the matching happens on your phone."

4.4 Concerns about COVID Alert

The participants expressed various concerns about COVID Alert, which we found were associated with their understanding of the app. Figure 6 illustrates how each aspect of participants' mental models is associated with specific concerns. In the rest of this section, we discuss their concerns.

4.4.1 Privacy Concerns. Only the participants with an *Unsound* mental model had privacy concerns. We classified these concerns as unjustifiable, as they were based on participants' incorrect belief that their location data is collected by COVID Alert for determining an exposure.

These participants expressed privacy concerns about the government using their location data for surveillance purposes (the red line in Figure 6). To illustrate, P16 stated: *"... the [location data] could easily be used for surveillance purposes [by the government] ... I just do not want to be traced."* The participants also worried their location data is collected and used by technology companies. By listing other app companies known for massively and secretly collecting users' data, participants expressed concerns COVID Alert does the same: *"[COVID Alert] says that they are not going to trace you. They are not collecting [users' personal] information ... but knowing the possibility with other apps that can collect your information, for example, Google [can have] your search activity ... Facebook can [trace users' location]. I think it is possible that [COVID Alert] collects [users' data], whether they would say it or not"* (P8). Further, P5 thought her location data are used by the app operator for its own benefits: *"I think the [app company] definitely has a copy of all users' [location] data and for its own purpose ... I do not like it."*

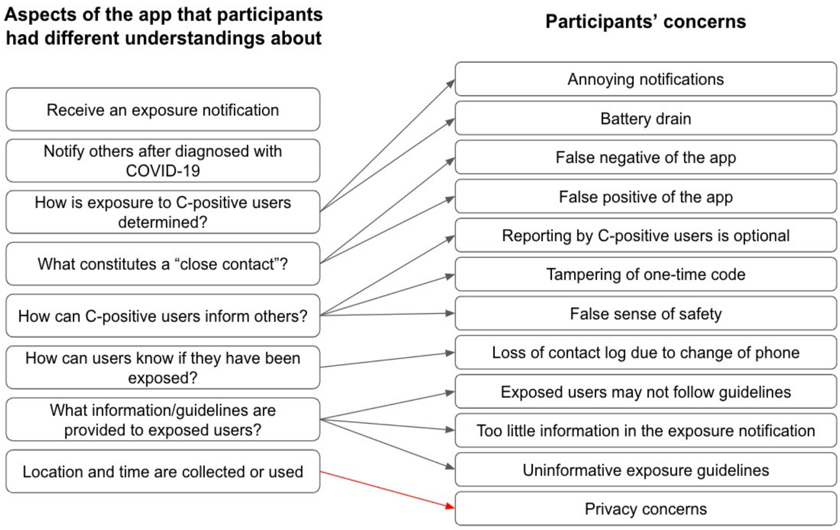

Fig. 6. A mapping between app aspects that participants have different understandings about and the concerns they expressed. The black arrows indicate the links between participants' accurate understanding and their justifiable concerns. The red arrow indicates participants' misunderstanding of certain aspects of the app, resulting in unjustifiable concerns.

4.4.2 Justifiable Concerns. We identified several concerns associated with participants' correct understanding of the app. In other words, participants had sufficiently complete and accurate understanding of the app to raise justifiable concerns.[5] For example, P8 knew about the information provided by exposure notifications and was concerned about its insufficiency. In the following, we report how participants' understanding of the app's aspects was associated with their concerns.

Concerns about Bluetooth for exchanging random codes with nearby phones.

Annoying notifications: Participants believed it unnecessary to keep Bluetooth on all the time. However, COVID Alert constantly reminds users to turn on Bluetooth and to keep the app active [121] even if the user is at home alone. For example, P1 said: *"I do not leave my house for a couple of days. [COVID Alert] sends me notifications [reminding me to] make sure you keep your Bluetooth on and keep the app open. And I am like, 'I am not going anywhere.' So it does get really annoying sometimes."*

Battery drain: Similar to previous findings [152], our participants believed having Bluetooth on affects their phone's battery. For example, P17 explained: *"... it says that you have to keep [Bluetooth] turned on if you want the app to work. But I notice that my [phone] battery drains fast."*

Concerns about what constitutes a close contact.

False negative of the app: Participants expressed concerns about the app's ability to handle corner cases. A few participants doubted the heuristics of detecting a close contact with an infected person. According to the US Centers for Disease Control and Prevention (CDC), close contact involves being within 6 feet of an infected person for at least 15 minutes [55]. However,

[5]Note that participants who misunderstood some aspects of the app could still have justifiable concerns rooted in correct understanding of other aspects.

there might be extreme cases in which people become infected at a greater distance from the patient or after a shorter contact time [9]. With correct knowledge of what constitutes a close contact, participants were worried the COVID Alert app may not be effective enough. They believed it cannot identify all cases of exposure, which results in false negatives. To illustrate, P1 explained: *"[The 2-meters-and-15-minutes rule] bothers me because I think if I am passing by someone, all of a sudden [that person] sneezes, and he does not cover his face, and he does not wear a mask, it can only take a second [for] him to infect me. [The exposure] is not going to take 15 minutes."*

False positive of the app: The possibility of the app having low accuracy was another point of concern. For instance, the app notified P15 about exposure to a C-positive user. However, she believed there was no way she had been in proximity for at least 15 minutes to anyone who was outside her bubble. She was frustrated about taking a COVID-19 test and being unable to go to work for a couple of days.

Concerns about users' notification of exposure.

Reporting by C-positive users is optional: Participants expressed concerns about the optional nature of uploading proximity identifiers by C-positive users. The effectiveness of the app depends on this step (a prerequisite to the detection of exposure cases) being completed promptly by as many C-positive users as possible. Two participants understood the optional nature of this step. Unsurprisingly, they were concerned exposed users would not be notified, if C-positive users chose not to proceed with this step. For instance, P9 commented that uploading proximity identifiers by C-positive users should be compulsory because if voluntary *"then what is the purpose of the app if not everyone is doing it?"*

Tampering of one-time code: After trying the app themselves, participants were worried other people could tamper with the app. Because participants were aware that C-positive users have the option to enter a one-time code to upload their contact logs, they worried there may be people who attempt to enter fake codes. To illustrate, P1 said: *"Some people might just enter a random or fake code. Like, playing devil's advocate, if there is a fake code or something, it [will] mess up the system. Some people are just mean that way."* We would like to note these codes are 10 digits long [137] and likely generated randomly. As such it is unfeasible to correctly guess a code.

False sense of safety: Having the COVID Alert app in use may give users a false sense of safety. Some participants acknowledged that C-positive users might decide not to notify their close contacts via COVID Alert. Hence, users exposed to those C-positive people would not be notified and therefore not get tested or obtain treatment sooner. If users assume all C-positive users notify their close contacts via COVID Alert, they would also assume they will be notified if in close contact with a C-positive person. Their assumptions would give them a false sense of safety, believing they are free from infection as long as they do not receive an exposure notification. Participants believed this false sense of safety might result in those users being careless and ignoring COVID-related precautions. P2 expressed this concern and explained: *"... if [the users] are carrying their phones all the time, and they expect to get [an] alert if they have been in close [contact] to somebody who tested positive for COVID, then they might drop their guard a little bit."*

Concern about the process of contact matching.

Loss of contact log due to change of phone: The unique aspect of the app is how and where the contact matching is done. Basically, from the central server the users' phones keep downloading the random codes generated and uploaded by C-positive users to see if the codes match with ones collected from nearby phones. The matching is, therefore, done locally. With this knowledge, P3 (who had an *Advanced* mental model) was concerned that switching to another phone would result in users losing collected codes. Such a loss may negatively affect the utility of COVID Alert. He explained: *"... [exposure detection] relies on the continued use of that app and the continued use of the same phone. So there will be situations [where] you got a new phone, and perhaps suddenly you will not be notified [if you were exposed]."*

Concerns about information/guidelines provided to exposed users.

Exposed users may not follow guidelines: Many participants were concerned exposed users might ignore the app's instructions and possibly spread the virus further. Participants were aware exposed users would receive a notification that would also include recommendations for next steps. They also acknowledged there was no way to ensure exposed users would follow the recommended actions. Hence, referring to the news that people do not always follow restriction rules [50], participants questioned the effectiveness of the app. They were concerned exposed users may not follow the suggested guidelines because they might not see the personal benefits in following them. To illustrate, P11 explained: *"I think the [COVID Alert app] has limited usefulness. I know we are doing [contact tracing] as an honour system, but I am aware of the news that not everyone is decent people. ... I think there are people who just ignore the notification ... maybe because they think they have better immune systems."*

Too little information in the exposure notification: COVID Alert does not provide exposed users with enough information about the exposure. Participants expected to be provided with a range of information by COVID Alert when notified of close contact with a C-positive person. Some participants were able to describe the suggested next steps in detail even though they had not received any notifications themselves, citing the COVID Alert official website [133] as their source. Two participants had received notifications before and vividly remembered their contents. Unsurprisingly, some participants expressed dissatisfaction with the provided information and questioned its usefulness, since it did not meet their expectations. For instance, P8 expressed a desire to learn about when and where the interaction happened, so he could *"conduct [his] own contact tracing"*(§4.2). After receiving an exposure notification, he was disappointed with the limited amount of information in the notification: *"[COVID Alert] does not give you what you think it is [going to] give you. So, it just tells you that you have been in close contact with a diagnosed person in the last 14 days. It does not tell you the day. It does not tell you the place. It does not tell you the time, and it does not tell you the person. So, it is kind of shocking when you read it."*

Uninformative exposure guidelines: With knowledge of the guidelines provided by COVID Alert to exposed users, participants found it too general and therefore unhelpful. For instance, referring to a screenshot P8 took of the exposure notification he got, he explained that the app suggested taking a COVID-19 test and self-isolating while waiting for the test result. He later questioned the usefulness of the guidelines. There were no instructions regarding the people around him (e.g., his family members and colleagues), such as whether they need to take a test: *"... because I know that I can possibly bring the virus back home."* Further, participants believed it may not be reasonable to follow guidelines under certain circumstances. For example, P19 brought up a scenario in which a user was wearing a mask when they were in close contact with a C-positive person and later received an exposure notification. He pointed out that having the user take a test in this scenario was unnecessary. However, the guidelines provided by the app are not made based on individual experiences. To illustrate, P19 stated: *"You probably do not need to take a test, but the app tells you to do it anyway ... like, there is no negotiation there."*

4.5 Strategies for Coping with Concerns

After a participant expressed a concern, we further explored their strategies for coping with it. These strategies included turning Bluetooth off most of the time, disabling the app, and accepting their concerns.

To mitigate their concerns about false positives and battery drain, some participants chose to turn Bluetooth off. For instance, P15 was dissatisfied with the false positive of the app (§4.4.2), so she turned off Bluetooth on her phone when she was off work. She explained: *"I have to use the [COVID Alert] for work, but I turn off the [Bluetooth] signal [when I am not at work.]"* P17, who was worried about the app draining his phone's battery, also would disable the app when at home.

At the same time, many participants did not change their behavior to cope with their concerns. We further explored their reasons for accepting the expressed concerns.

Privacy-utility trade-off: For participants who had privacy concerns, they believed they had to make a privacy-utility trade-off. For instance, although P5 had concerns about her location data being collected by COVID Alert, she continued using the app. She explained: *"[Providing location data to the app] is something that we have to do. Like, otherwise, how would the app know we have been in contact with some patients? ... It is necessary for the [COVID Alert] app to keep [my location information]."* Another participant, P17, was also willing to accept the privacy-utility trade-off and said: *"I do not like to be tracked. But I am not so naive to think that other apps are not also tracking me. So I do not mind the government tracking me for my benefit."*

Better than nothing. Even though the app did not meet all their expectations, several participants decided to continue using the app. Some participants were unsatisfied with COVID Alert and questioned its usefulness, such as its limited information to exposed users and optional uploading of data by C-positive users (§4.4.2). However, they further acknowledged that at least the app can provide one function: letting them know whether they were in close contact with a C-positive person. For instance, P11, who criticized the limited information the app provides to C-positive users, further stated: *"I wish [COVID Alert] was better. There are a lot of flaws in it, but [COVID Alert] is all we have got for contact tracing."*

4.6 Centralized vs. Decentralized Design

Participants did not express a preference for either a centralized or decentralized design of exposure-notification apps. Two recent quantitative studies [100, 204] identified a link between a contact-tracing app's design for data collection and handling and the public's willingness to adopt it. In our study, we sought to investigate not only what people prefer but also *why* they prefer it. Our results suggest that, even though our participants had already adopted the COVID Alert app, most of them were okay with using a centralized app too (corroborating the survey findings of Li et al. [99] that the data structure of a contact-tracing app does not affect people's intentions to adopt it). As described in §4.3, most participants' mental models of COVID Alert did not include the mechanics of exposure detection. Similarly, when asked about a centralized vs. decentralized app, most participants did not care about this aspect. Instead, participants paid more attention to (1) the need to provide a personal phone number to use the centralized app and (2) how they will be notified if exposed to COVID-19.

Participants favorably viewed the human element of a centralized contact-tracing app. First, participants expected to gain more personalized information through a phone call with health authorities, who could provide answers to their questions and offer guidance on next steps. For instance, P16 believed if she were notified of exposure through a phone call instead, she could provide more personal information to the health officials, which could help her get answers about her personal situation: *"[The health workers] can answer my real questions. I can give them more information, like I have asthma, like I am immunocompromised and I live with my grandmother. Am I at high risk? Should I go to see my doctor?"* Second, some participants believed involving health authorities in notifying exposed users would make the procedure more efficient and better enforced. For instance, P7 explained: *"[A phone call from health authorities] would be harder to ignore than just getting a notification on your app. If you are talking to a person, you are kind of forced to be more active in responding to the information and taking action."* However, this opinion of P7 was in contrast to those of some other participants.

Several participants preferred the higher level of privacy protection, the choice of cooperation, and the more efficient notification delivery method in a decentralized contact-tracing design. As explained previously (§4.3), our participants' mental models of COVID Alert did not include any explanation of the app's data architecture (except for P3, as described in §4.3). In other words, participants did not understand whether the app is decentralized or centralized in how and where the code matching is done. As a result, when comparing a decentralized app with a centralized one, participants perceived the an app's privacy from its collection of users' information. For instance, P4 believed a decentralized app offered more privacy because it does not require users to provide their personal phone numbers. He explained: *"I like [COVID Alert app] better because it protects my privacy more. It does not collect my phone number."* P2 preferred a decentralized app because she believed that, unlike a centralized app, it provides a choice about whether to cooperate with contact-tracing procedures: *"The thing about a phone call is [the health officials] are going to keep following up to make sure I go get a test. Well, that decision should be mine, right?"* Furthermore, P9 expressed more confidence in a decentralized app because it provides more accuracy in the tracing: *"I could imagine [COVID Alert] provides more accuracy as we allow the computers to do all the analysis [and] automatically send out notifications."*

5 DISCUSSION

5.1 Limitations

Our study has four limitations. First, since our participants used a decentralized exposure-notification app, we presented them with a description of a centralized version. As such, their answers regarding it reflect self-reported perceptions, attitudes, and intentions. However, we explored participants' reasons for preferring or being concerned about the centralized app. We believe their answers would likely align with their actual behavior. Second, like any qualitative investigation using a diverse sample, our study did not offer quantitative conclusions generalizable to the target population. Third, since our participants were recruited in Canada, the results of this study would need to be validated and refined in the contexts of other countries. Fourth, we did not observe any associations between participants' demographic information and their concerns. A future large-scale quantitative study may bring more insight to this potential link. Nonetheless, this study lays the groundwork for further investigations of mental models, expectations, experiences, and concerns shared by users of exposure-notification apps.

5.2 General Discussion

To the best of our knowledge we conducted the first *qualitative* study that investigated the perspectives of contact-tracing app users regarding the app. Our study focused on their understandings of the app, their concerns about it, and their fulfilled and unfulfilled needs for it. Studying real users' ongoing experiences enabled us to identify strong and weak aspects of the app. Most importantly, compared to many quantitative studies [7, 8, 34, 47, 75, 100, 109, 110, 114, 146, 148, 175, 177, 185, 188, 189, 204], our use of qualitative methods allowed us to investigate not only the whats but the *whys* of users' concerns, and their met and unmet needs regarding the app. As a result, we contribute to the body of knowledge in unique ways. Given the richness of our findings, we suggest new research directions and offer recommendations for improvement to various stakeholders (discussed in later sections).

For instance, in addition to corroborating previous findings that users consider privacy protection regarding exposure-notification apps [2, 3, 7, 31, 75, 89, 100, 142, 152, 197, 204, 207], we also discovered that participants' privacy considerations were linked to their knowledge of the app's data practices (which is different from experts' views of privacy risks). Particularly, participant focus was on the personal information required to conduct the contact tracing and to receive exposure notification rather than on the app's decentralized data structure. Given this discovery, we recommend (§5.3.2) that technology developers and operators increase transparency about their data practices in order to help build public trust in them. Further, our findings about the connection between users' understandings of the app and their concerns contribute new insights about users. These insights can help mitigate user concerns, such as assisting users to build adequate and relatively complete mental models (§5.3.4).

We also explored participants' motivations and expectations for learning about their exposure to COVID-19. Building on many previous studies [6, 17, 39, 41, 53, 76, 102, 138, 140, 143, 182, 191, 197, 204], we make design suggestions that can possibly better meet users' expectations and bring more societal benefits. For instance, providing a more detailed exposure notification to exposed users can save public resources. It can also potentially manage the spread of the virus by enabling the exposed users to better conduct their own contact tracing (see Recommendation 1 in §5.3.1).

5.3 Recommendations

5.3.1 Trade-Off between Privacy and Utility. A consensus on how to reconcile the privacy-utility trade-off in exposure-notification apps has yet to be reached. The apps are positioned to help manage the COVID-19 pandemic. Their effectiveness largely depends on the adoption rate [54, 74, 139]. At the same time, privacy and security concerns have been identified as factors contributing to the low adoption of such apps in many countries [2, 3, 7, 14, 23, 70, 75, 89, 91, 100, 152, 161, 189, 204]. Unsurprisingly, the academic community has been busy conducting studies to investigate the public's perception of exposure-notification app aspects: the privacy and utility of app architectures (e.g., centralized vs. decentralized); app providers; data practices; and app benefits [98, 100, 152, 166, 169]. However, there is no consensus on the app design that hits the sweet spot in the privacy-utility trade-off. COVID Alert is perceived as trading some necessary utilities to protect users' privacy.

Reduced utility of the app due to perceived uninformative exposure notification. The value of COVID Alert in limiting the spread of the virus appears to have been traded for its protection of users' privacy. COVID Alert exposure notifications only inform exposed users of close contact with a C-positive user sometime during the last 14 days [128]. Such limited (and unhelpful for our participants) information in the notification is a result of sacrificing utility for the sake of exposed users' privacy. Specifically, without the app informing when and where the interaction might have happened, participants could not identify members of their contact circle that may subsequently have been infected nor estimate the likelihood of them being infected (§4.4.2). For the app to be effective while providing such limited information about the exposure, the majority (60%) of the population would have to use the app [54]. However, as with most exposure-notification apps, COVID Alert is far from this level of popularity, with our estimate at around 20% (based on the number of downloads [122, 171]).

Recommendation 1: App developers should provide exposed users with the time and place of exposure to improve the app's utility. This additional information would enable users to conduct their own contact tracing, significantly increasing the app's utility to the community and reducing the costs of contact tracing by the health authorities, all without the prerequisite of wide adoption.

A better balance between privacy and utility could be reached by giving users more control over their data. For example, COVID Alert could give an approximate time of exposure. As explained in §2.1, COVID Alert exchanges proximity identifiers via Bluetooth and stores them locally for 14 days. A new proximity identifier is generated every 5–20 minutes. The app implementation (or the underlying libraries) could record the time when each proximity identifier is received, therefore making it possible to narrow down the time of exposure to a C-positive user. C-positive users could be given control over whether and with which granularity (e.g., minutes, hours, or days) the time stamps of matched proximity identifiers are made available to other users.

At the same time, C-positive users should be made aware of the risks (e.g., de-anonymization) of increasing the granularity of time stamps. C-positive users should also be made aware of the benefits of providing time (and other information) to exposed users. Those benefits include enabling exposed users to better estimate their risks, to perform their own contact tracing, and to take the most appropriate next steps. Hence, C-positive users could be given the opportunity to evaluate the trade-off between personal privacy and utility for others. Sharma et al. reported that individuals were more open to sharing their personal data when informed of its use by contact-tracing apps [167]. Additionally, our results suggest that some participants were willing to share their identities with people they had been in close contact with (§4.2).

Suppose a C-positive user believes the benefits of sharing their information outweigh the privacy costs and is willing to make the trade-off. In that case, they could consent to including more details of the exposure in the notification, to better support the exposed users. With the C-positive user's consent, the app could present exposed users with details like *"You have had contact with someone who reported a COVID-19 diagnosis through this app. The interaction happened on April 4, 2021."*

Going one step further, technology could attach approximate location data to proximity identifiers. C-positive users could be given a similar choice of revealing this information. As people value privacy and benefits differently (individual and societal) [195], users could have the power of choosing their own privacy-utility trade-off. Before they decide whether to share the information, the possible risks and benefits should be made clear to them.

Reduced utility of the app due to critical steps being optional. The optional aspect of critical steps in COVID Alert's workflow was perceived as a significant barrier for public health. This specific design of the app is an example of trading some utility for users' privacy. As explained in the privacy assessment of COVID Alert [123], the Canadian government has no way of knowing who received a one-time key to enter in the app. So, there is no way of knowing if C-positive users have uploaded their proximity identifiers, necessary for triggering exposure detection. Further, those users who get an exposure notification are not required to do anything about it (e.g., get tested or self-isolate). As a result, while appreciating the freedom of choice, participants raised concerns about the effectiveness of COVID Alert (§5.3.1). For instance, although they indicated they would do the right thing, participants were concerned others might not upload their proximity identifiers when diagnosed or follow the guidelines when exposed. This concern led to participants' dissatisfaction with the app and their questioning of its value to the community.

Recommendation 2: All stakeholders should increase the motivation for C-positive users to notify the app and for exposed users to follow the guidelines. As an example, better public communication could be made regarding two aspects of COVID Alert. First, motivate C-positive users to upload their contact logs and explain that associated privacy risks are low. These logs remain unknown to the health authorities, and the possibility that other app users could identify C-positive users is estimated to be very low [44]. Clearer communications could assure C-positive users that their privacy is protected and ease the concerns of potential users about stigma [6, 17, 76, 138, 140, 182, 197, 204].

Second, educate users on the community benefits of uploading proximity identifiers when C-positive (e.g., reopening the economy, and empowering exposed users to do something about the exposure). Studies show that people typically have a natural willingness to help others in need, especially when they are directly asked [67, 92, 165]. Therefore, public communications could emphasize how C-positive users can help others. Moreover, as people are more inclined to help others when they have a strong sense of a shared identity and goal [48, 49], public communications could indicate how the app can help achieve a shared societal goal (e.g., reopen society).

5.3.2 Trust in App Providers. Technology companies were not considered trustworthy providers of contact-tracing apps. Trust is a fundamental element in the customer-company relationship [147], and many studies suggest there are growing concerns about technology companies mishandling users' personal information [36, 66, 131]. Specifically, low trust in big technology companies has been identified as hindering the adoption of contact-tracing apps [131]. Our findings share a similar sentiment. Participants with an *Unsound* mental model distrusted the technology companies as COVID Alert providers because of their data practices (§4.4.1).

Recommendation 3: App designers and developers should build and maintain the public's trust. Providing data transparency could be a good way to start [39, 41, 53, 102, 143, 191]. For example, contact-tracing app companies could help the public better understand their data collection, retention, and sharing practices [78, 95]. The companies could present specific, transparent, and easy-to-understand information to the public. For example, people could be clearly informed which entities have access to the information collected from users (e.g., a C-positive person's uploaded random codes), the purpose for accessing that information, and the retention of users' data (e.g., C-positive users' random codes will be deleted after 15 days [124]).

Another way to help build trust is to provide users with more control over their data and make them aware of that control [39, 153, 174] (see our Recommendation 1 in §5.3.1). Additionally, users could be clearly informed of their authority to delete exposure logs from their phone's settings at any time [124].

5.3.3 Helpful Guidelines. Generic guidelines were perceived as unhelpful. Some participants believed the guidelines provided by COVID Alert to exposed users were too general, provided no specific details, and were unnecessary in some cases (§4.4.2). For example, the first recommendation in these guidelines is to take a COVID-19 test [133]. However, participants believed a test was unnecessary for exposed users wearing masks when in close contact with C-positive users. Although wearing a mask can reduce the risk of being infected [10, 97, 103], it does not eliminate that risk [30]. Many factors can influence virus transmission, such as ventilation and the airflow's direction and intensity [30]. At the same time, some participants preferred the idea of a conversation with health officials to get personalized advice on next steps if they receive an exposure notification (§4.6).

Recommendation 4: App designers and developers should provide more details in the app's guidelines. For example, taking a COVID-19 test, even before symptoms arise, could be further explained as a necessary first step after exposure. The guidelines could also explain that wearing a mask all the time does not protect users from the virus because C-positive people might not wear masks or may wear them improperly [108]. Additionally, more guidelines about exposed users' families, workplaces, and schools could be provided. For instance, exposed users could be told whether their housemates need to be tested or quarantined (with or without showing symptoms). Information about the legal responsibilities of exposed users to inform employers [129] could also be provided to remedy some confusion and help manage the possible spread of the virus.

5.3.4 Users' Mental Models, Concerns, and Coping Strategies. Participants with different mental models used COVID Alert in similar ways. That is, they kept the app running in the background. None of them had used the app to notify others. We attribute the lack of reported differences in behavior to two aspects: the very limited set of user interactions accepted by the app, and the lack of significant effect of users' mental models on their performance, as suggested by other studies [21, 28, 69, 163]. We did, however, observe differences in concerns.

Participants with an *Unsound* mental model had unjustifiable privacy concerns and unrealistic expectations about the app's functionality. Previous studies have suggested that users' mental models can be incomplete, unstable, and/or contain misconceptions and even aspects of superstition [117, 201]. Likewise, our participants with an *Unsound* mental model believed the app collected their location data. Due to this misunderstanding, participants expressed privacy concerns regarding their location data being collected and used by the government and/or the app provider. Further, to cope with the concerns, participants adopted a strategy of helplessly accepting the privacy-utility trade-off offered by the app (§4.5). Because only participants with an *Unsound* mental model misunderstood some aspects of the app, they were the only group in our sample who expressed privacy concerns. Even with a correct understanding, users with an *Unsound* mental model could still have concerns, albeit different ones (see P2's concern about the false sense of safety in §4.4.2). Unrealistic expectations were also a trait of an *Unsound* mental model. Some participants believed the app could inform them in real time when a C-positive user was nearby. Such unrealistic expectations might possibly result in dissatisfaction with the app in future.

Participants with an *Innocent* mental model did not express any concerns about the app. This is particularly intriguing given how little they understood the app compared to the rest of the sample. We do not have data to know for sure the reasons for their lack of concern, but their mental model might not detailed enough to raise a concern. In other words, participants may not have enough knowledge about the app to have a point of view. While it may seem like these participants are happy campers, the lack of detail in their understanding of the app may cause problems later. For instance, previous work suggests that the completeness of a mental model matters [88, 93, 117]. Specifically, users with inadequate mental models may lack the ability to deal with unexpected situations, especially when things go wrong. In our case, participants with an *Innocent* mental model had a very limited understanding of the app and saw no need to learn more about it. However, difficulties may arise when unexpected things happen with the app, such as suddenly receiving an exposure notification. Given how concerned and frustrated other participants felt about insufficient and uninformative exposure notifications, users with an *Innocent* mental model may feel lost when they eventually encounter the app's notifications.

More nuanced and accurate mental models enabled participants to raise various justifiable concerns. Participants with a *Structural* or *Advanced* mental model had a more adequate and relatively complete understanding of the app, resulting in justifiable concerns about COVID Alert. These concerns, however, did not turn them away from it because using the app was better than nothing (§4.5).

Recommendation 5: App designers and developers should explain the app's key elements to help users form more adequate mental models. Previous studies suggest that learners' more detailed misunderstandings of an app can be beneficial. The aspects they have trouble understanding can reveal users' learning processes, which in turn can help developers determine the necessary design modifications [170]. For example, participants with an *Unsound* mental model had an inaccurate threat model, which led them to believe a privacy-utility trade-off was necessary (§4.5 and §4.4.1). To mitigate their unjustifiable concerns, we propose helping users develop a more adequate mental model. Conventional and common ways to help them form more adequate mental models include providing instructions, training, labels, tutorials, and visual cues [15, 56, 85, 159, 184].

Once built, mental models can be surprisingly hard to change, even when people are aware of contradictory evidence [178]. One possible way to influence users' mental models is to highlight common misconceptions [101]. A walk-through is currently implemented to help COVID Alert users understand how the app works when they first open it. This walk-through highlights that users' location data is not being collected [123]. Yet some participants developed an *Unsound* mental model. Therefore, we suggest presenting users with explanations about common misconceptions, rather than just listing them.

Mental models may evolve if users integrate new observations into their reasoning [101]. Previous studies suggest users may adjust their mental models if the system makes its reasoning transparent, such as the purpose of accessing a certain type of users' information [72, 93, 94, 101, 172]. We therefore suggest users be provided a detailed explanation of the app, such as the reasons for data collection or lack of thereof, to help them form or evolve a more adequate mental model. For instance, some participants believed the only way to identify close contacts is by collecting location data. The app UX could explain how close contacts are identified without such information. The explanation should be direct and easy to understand, without too much jargon [27, 115, 144]. However, the effectiveness of such an explanation requires future research. Meanwhile, participants with an *Innocent* mental model should also be helped to develop a more complete understanding of the app. With an adequate mental model, participants can better learn the app's utilities and limitations and manage their expectations of the app, especially when unexpected things happen.

5.3.5 Centralized vs. Decentralized. Participants' perspectives about the privacy of centralized and decentralized apps were not exactly the same as experts' views on them. Many security experts have argued that a decentralized approach is a better choice for attracting users because it can offer greater protection against abuse and misuse of the public's data than apps that centralize data processing [4, 59, 168, 177, 183]. However, this particular benefit was neglected by our participants as most did not have a comprehensive understanding of the architecture of this approach and therefore lacked an appreciation of its value. Even though several participants believed a decentralized app would provide more privacy, these perceptions were mainly based on the idea that users' personal information was not collected by the app rather than on the app's decentralized processing of the data (§4.6). Notably, centralized contact-tracing apps have often been criticized by the public and experts due to privacy issues [33, 79, 111, 156]. However, most participants did not see centralized apps' privacy risk as a big issue for them. Some believed their phone numbers were not private information, while others trusted the government and health authorities to manage that information.

Each approach offers a unique benefit-risk trade-off, which was acceptable or even preferable for our participants. Although our participants had already adopted the decentralized COVID Alert app, most of them were okay with using a centralized app too (§4.6). Besides the privacy consideration (the most heavily debated aspect of contact-tracing apps [11]) our participants also considered other unique aspects of each approach. Specifically, the human elements of the centralized app were appreciated by participants, while the freedom of cooperation and more efficient notification delivery method of the decentralized app were preferred (§4.6).

Recommendation 6: All stakeholders should explain the benefit-risk trade-off the app provides. From a technical perspective, there is no perfect approach that is effective, guarantees privacy, and offers protection from cyberattacks [4, 96]. For instance, centralized systems tend to put the privacy of all users at risk, while decentralized systems tend to put the privacy of C-positive users at risk [4, 96, 183]. Consistent with a previous quantitative study [99], our participants did not express uniform preferences, i.e., a general public preference, for either centralized or decentralized apps. Hence, neither of these two approaches is preferable over the other.

Most stakeholder effort should, therefore, be aimed at motivating the public to actively use the chosen approach rather than at choosing an approach. Perceived individual and societal benefits have been identified as factors that could motivate the public to adopt a contact-tracing app [3, 89, 98, 152, 167, 177, 188, 189, 197, 198]. Additionally, prospective users are believed to calculate the costs and benefits of an app before deciding whether to use it [98, 152, 176, 197].

We suggest that, once a certain approach is chosen for use in a region or country, the benefit-risk trade-off should be made clear to the public. For instance, if a centralized contact-tracing app is chosen, stakeholders should clarify the possible risks for users (e.g., risk of personal contact information being leaked). The risks should also be justified by highlighting the individual and societal benefits of the chosen approach, especially the benefits for which the user's risk-taking is being traded (e.g., personalized guidelines can be provided if the user's personal information is collected). Additionally, stakeholders should be explicit about efforts to limit the risks (e.g., user information is encrypted and stored in a secure server) and estimate the risks to help users better manage their expectations and possible concerns.

5.4 Future Research

Future studies could take four directions to build on our research. First, a study could be conducted to determine users' and experts' views of the exposure notifications and guidelines provided by different contact-tracing apps (e.g., readability). Second, a study specifically aimed at understanding why some users have *Unsound* mental models of COVID Alert could provide more insight for the future design of such apps. A third avenue for research could be twofold: investigate ways of aiding users with *Unsound* and *Innocent* mental models to develop an adequate understanding of the app [200], and then see whether their perceptions of the app change and if they have new app concerns or expectations resulting from their updated understanding. Fourth, a within-subjects study could be conducted to better examine participants' preferences for centralized or decentralized contact-tracing apps [16]. Specifically, with real experience of both types of app and a comparison between the two, users may value the trade-off of each app differently.

6 CONCLUSION

We conducted 20 semi-structured interviews with users of COVID Alert, a decentralized exposure-notification app. We explored their expectations, mental models, and concerns about the app. Our results suggest that if users have been notified of close contact with a C-positive person, they expect more information than currently provided by COVID Alert. Participants' particular concerns are also associated with their understanding of certain aspects of the app. Compared to a centralized proximity-based exposure-notification app, COVID Alert was favored for its higher level of privacy protection, optional level of cooperation, and more efficient notification delivery method. At the same time, a centralized proximity-based exposure-notification app was preferred for its human elements. Based on our results, we suggest decision-makers rethink the app's privacy-utility trade-off and improve its utility by giving users more control over their data. We also suggest technology providers consider prioritizing the trust of users. In addition, more efforts should be made to motivate C-positive users to report their diagnosis and to encourage exposed users to follow guidelines. Moreover, the app's benefit-risk trade-off should be highlighted for current and potential users to manage their expectations and concerns. Finally, more effort should be made to help users with *Unsound* and *Innocent* mental models better understand the app.

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