Exploring Privacy and Incentives Considerations in Adoption of COVID-19 Contact Tracing Apps

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Abstract

Mobile Health (mHealth) apps, such as COVID-19 contact tracing and other health-promoting technologies, help support personal and public health efforts in response to the pandemic and other health concerns. However, due to the sensitive data handled by mHealth apps, and their potential effect on people's lives, their widespread adoption demands trust in a multitude of aspects of their design. In this work, we report on a series of conjoint analyses (N = 1,521) to investigate how COVID-19 contact tracing apps can be better designed and marketed to improve adoption. Specifically, with a novel design of randomization on top of a conjoint analysis, we investigate people's privacy considerations relative to other attributes when they are contemplating contact-tracing app adoption. We further explore how their adoption considerations are influenced by deployment factors such as offering extrinsic incentives (money, healthcare) and user factors such as receptiveness to contact-tracing apps and sociodemographics. Our results, which we contextualize and synthesize with prior work, offer insight into the most desired digital contact-tracing products (e.g., app features) and how they should be deployed (e.g., with incentives) and targeted to different user groups who have heterogeneous preferences.

1 Introduction

The outbreak of the COVID-19 pandemic was followed by the emergence of many new technologies aimed to help fight the pandemic. Among these, the primary one deployed across the world are mobile contact tracing applications. These applications are smart-phone based, and inform users of possible exposure to people who tested positive for coronavirus.

Like other mobile health (mHealth) applications, contact-tracing apps collect personal information and have inherent privacy risks despite many deployed apps using a privacy-preserving design [5, 60, 62]. Critically different from most technologies people adopt, however, the primary benefactor of contact tracing apps is the community rather than the individual. While knowledge of COVID-19 exposure may somewhat benefit individuals, for example so they can avoid exposing those they love, there are no steps they can take to protect themselves once being notified of exposure.

To ensure their effectiveness, contact-tracing apps need to be widely adopted [18]. However, in many countries, adoption was lower than hoped, demonstrating that encouraging users to adopt these apps is a difficult and multifaceted problem [48].

The challenge of encouraging the adoption of mHealth technologies is not limited to COVID-19 contact tracing apps. A myriad of mHealth apps have been introduced in recent years, ranging from steps-trackers, to mobile feminine technologies to track menstrual cycles, to social networks intended for those suffering from unique health conditions, and more. The adoption of such tools relies on potential users' privacy concerns, the incentives to install the app, and the tool's efficacy in achieving the eventual outcome of interest.

When designing such tools, understanding the preferences of potential users can allow developers and official entities to design more desirable products. Once developed, a marketing message that emphasizes the most important features of the product is needed to increase the likelihood of adoption [14].

The COVID-19 pandemic, with its disastrous impacts both locally and globally, is an important case study to explore the adoption of privacy-sensitive apps in the health domain. Thus, in this work, we study contact-tracing apps to understand the role of privacy, costs, incentives of either monetary or non-monetary nature, and their efficacy influence adoption.We take the lessons learned here to discuss future developing and marketing of health applications more broadly, noting that each health context has unique factors that require further investigations.

Specifically, we answer the following research questions:

RQ1 What is the role of privacy relative to other adoption considerations when deciding whether to adopt COVID-19 contact-tracing apps?

RQ2 Do consumers with different levels of receptiveness to installing such apps differ in their adoption considerations?

RQ3 When offering extrinsic incentives:
  (a) What is the role of these incentives relative to other adoption considerations?
  (b) Do they affect overall people's willingness to adopt these apps?
  (c) Do consumers' sociodemographics and their different levels of receptiveness to installing these apps influence their adoption considerations?

To answer these questions, we conduct an online randomized conjoint study (N=1,521). Conjoint methodology is a common method for product development and market share analyses in which participants make a series of choices between products with differing features. This methodology allows the researcher to understand the importance of different attributes in the developed product – those attributes that are usually *considered jointly* when choosing whether or not to adopt (e.g., purchase, install) the product. Conjoint estimates allow researchers to investigate which product attributes are more important to a potential customer and at what levels. In addition to employing conjoint methodology, we build a unique randomized study atop it to investigate the factors people take into account when considering adoption of COVID-19 contact-tracing apps.

In particular, we investigate three types of incentives that were proposed by countries and states to encourage the adoption of contact tracing apps: intrinsic motivation (e.g., to protect the self or others), monetary compensation (in the form of a gift card) and health incentives (multiple options of health care coverage). We investigate the privacy considerations people have when choosing whether to adopt contact-tracing app (RQ1), the effect of the various incentives on people's overall intent to adopt (RQ3a), the importance of incentives relative to the other attributes – privacy concerns, data storage location, accuracy and more (RQ3b), as well as how people's receptiveness to installing the apps [22] (RQ2) and their sociodemographic attributes intersect with their feature importances and response to incentives (RQ3c).

By answering our research questions, we provide (a) principles regarding how future privacy-sensitive health technologies like contact-tracing apps should be built to best appeal to users (i.e., based on the features considered to be most important), (b) principles on how to market such technologies, and (c) first evidence of how each individual incentive may alter the decisions people make when it comes to privacy and accuracy considerations.

Ethical Considerations. Before conducting our study, we obtained approval from our institution's Ethical Board Review committee. Participants gave their consent to participate in the study. We collected the participants' demographic information for the study purpose, such as age, gender, and education level, but did not collect identifiable information such as name or email address.

2 Related Work

2.1 Contact-Tracing Apps

To fight the COVID-19 pandemic, many countries developed and deployed contact tracing apps. The main objective of these apps is to trace people's interactions with others and alert them in case they may have been exposed to the coronavirus. The design of contact-tracing apps has both ethical and practical implications. To ensure its effectiveness, at the minimum, the app requires detailed information about a person's interactions and specific health-related information (i.e, COVID-19 test results). Thus, ethical considerations need to be taken into account when designing these apps, to balance the app's benefits – reducing the spread of the virus – and harms, such as privacy risks [46]. Indeed, different types of contact-tracing apps were developed around the world, with these differences considered among the most prominent ones: 1) whether they were centralized or decentralized; and 2) whether they collect location or proximity data (or both). These attributes exemplify the trade-off between benefits and harms, where the design that is considered as more privacy-preserving poses more challenges to the health authorities to control the spread of the virus.

2.2 Adoption Considerations of Contact-Tracing Apps

The success of contact-tracing apps heavily depends on the proportion of the overall population that install [18] and appropriately use [3] these apps. The more people who install the app, the better, as this allows more interactions to be traced. However, as these apps were launched, the adoption rates were not sufficient in many countries. While in some countries the adoption rate was relatively high, such as Iceland, with 38% adoption rate in the first month [42], in other countries the numbers were far lower. For example, approximately one month following the apps' deployments, the adoption rates were 24% in Australia [1], 19% in Germany [57], 12% in Italy [16], and only 3% in France [19].

Motivated to increase adoption of contact-tracing apps, many studies were conducted to explore people's willingness or intent to adopt these apps through surveys, such as [36, 49, 64] and field studies, such as [17, 43], and the relationships between the explored factors. While a wide range of variables were explored in different studies, for the purposes of this review, we focus only on those that are closely related to the current study.

Privacy concerns. Previous studies found a positive relationship between intention to adopt and the extent to which the app is privacy-preserving, either based on participants' perceptions [59], or based on information provided about the app [10, 21, 30, 36, 44, 56, 63]. Prior work also explored the effect of the app's architecture, specifically its centralization mechanism. Here, studies point to contradicting results, in which participants preferred a decentralized architecture in some studies [10, 44, 65], and a centralized one in others [30, 38, 39]. Studies also explored the effect of the collected data – location, proximity, or both – on intent to adopt. Again, the results were inconsistent: some studies found that people preferred proximity-based apps [49], others found preferences towards location-based apps [38, 39, 49, 63], and others found similar preferences across the options [30, 65].

Benefits. There are two main functions across the different types of contact-tracing apps: notifying users in case of an exposure to someone who tested positive to COVID-19 (individual benefits), and helping the general population to reduce the spread of the virus (societal benefits) [49]. According to privacy calculus theory, users weigh privacy risks against earned benefits [13]. Applying privacy calculus theory, Hassandoust et al. found that benefits were positively associated with the intent to adopt, while privacy risks had an opposite, weaker relationship [29]. Other works also found a positive association between benefits and adoption [36, 44, 49, 64], and that these benefits have a stronger effect than privacy in adoption decisions [38].

Direct incentives. Several studies explored the role of offering different types of benefits that go beyond fighting the pandemic. In general, these incentives were either direct, tangible incentives, such as monetary compensation [21, 32, 35], or individual "extra" benefits that either *prioritized* app users over non-users [10, 63] or *restricted* something from happening unless the app was used [10, 63]. For example, participants were willing to adopt an app that prioritized app users to get tested for COVID-19 [10, 63] or allowed them to interact with others when a lockdown was not in force [32, 35]. On the other hand, users were less willing to adopt an app if using it was a prerequisite for returning to work [10, 63].

The use of monetary incentives to increase pro-social behavior has been examined [7, 24], providing theoretical support for using such incentives to increase app adoption. However, findings also show that offering monetary incentives can result in the opposite outcome [24] and in "crowding out" intrinsic motivations to behave pro-socially [20].

In the context of contact-tracing apps, studies have discussed offering financial incentives, either supporting such an intervention [58] or suggesting concrete ways to conduct it ethically [40]. Prior experimental studies showed that people valued monetary incentives to different extents depending on the study's context. For example, in two conjoint studies, a monetary incentive was found as the most important attribute [21, 35]. On the other hand, a different study found that participants cared more about their ability to interact with others than getting paid for using the app [32]. Previous field studies also point to the positive effect of monetary incentives on adoption, in which two field studies in Germany found that offering money (€1, €2, €5 in [43], €10 in [17]) increased the adoption rate among the incentivized participants.

Efficacy - how well the app performs. Prior work explored the effect of an app's accuracy on people's intent to adopt [21, 36]. While both studies found a positive effect, Frimpong and Helleringer found that its effect was smaller relative to monetary incentives [21].

Costs. A few studies have explored the effect of the app's costs, such as draining the phone's battery, and found a negative effect on intent to adopt [38, 49].

Contact-tracing app adopters. Prior work examined differences among potential users. Exploring the installation of SwissCovid, the Switzerland COVID-19 App, Geber and Friemel [22] used a typology-based approach and defined four types of people: refusers, ditherers, adopters, and de-adopters. They found significant differences in adoption considerations among these types. For example, adopters rated health benefits significantly higher than all other types of potential users.

2.3 Research Gap

While prior works, particularly field experiments or those employing a choice-based methodology similar to our own, have explored some of the variables in our study, several questions remained unanswered:

Controlled direct incentives. While prior work explored the role of monetary incentives in people's adoption decision [17, 21, 32, 35, 43], there are two main gaps here: 1) monetary incentive was the only explored direct incentive, whereas governments were actively considering health benefits; 2) if monetary incentive was included, participants were always presented, or potentially presented (if in a field study) with monetary incentive, even if set to zero (or even presented with the option to pay for use, instead of receiving compensation [21]). When people are presented with both financial and non-financial incentives, or when they are presented with free and paid products, they might alter their perceptions in ways that cannot be teased apart [8, 9]. In our study, therefore, we incorporate a randomization on top of the classic conjoint design to mitigate such potential biases. Moreover, we also explore incentive different from money (healthcare-related).

Costs. Costs considerations were not explored in previous choice-based studies. Therefore, we seek to learn how people prioritize these considerations relative to others.

Privacy. Prior works have not explored privacy considerations alongside potential costs and benefits. As we worked closely with app designers, we added multiple considerations and privacy aspects that, along with the analysis of incentives and costs, can shed light on the economics of privacy for contact tracing and other mHealth apps.

3 Methods

Conjoint analyses are usually conducted to learn which products are worth developing and at what price point. Additionally, such analyses can inform how best to market the resultant product. In the case of COVID-19 contact-tracing apps, countries and health authorities were eager to understand which app attributes were most important to potential users and how to encourage adoption. Our conjoint analyses tested the importance of seven attributes of contact-tracing apps identified as potential user considerations in prior work [6, 39, 48, 56]: the accuracy of the app in identifying exposures to coronavirus; the benefits of the app; the privacy aspects of the app, specifically a) what data the app collects, b) where that data is stored, and c) the privacy risks from potential leakage of app data; and the costs of the app in terms of a) mobile phone data usage and b) battery life.

While our application was COVID-19 specific, the methodology we use - conjoint analysis - and the randomized layer on top of it, which allowed us to cleanly identify the role of incentives in adoption considerations, may be used to inform developers of other mHealth apps and privacy-related apps of other forms. Therefore, we describe the methodology in detail.

Below, we describe the specifics of the survey that we used to conduct these choice experiments and how we analyzed the data collected from our survey instrument.

3.1 Study Design

We randomly assigned participants into three different conjoint studies, in order to cleanly test the effect of different types of incentives on installation considerations: intrinsic incentives (hereafter, intrinsic survey), healthcare incentives (hereafter, healthcare survey), and monetary incentives (hereafter, monetary survey). We did not evaluate different types of incentives in the same survey because this might create reference-dependencies between the extrinsic incentives and the intrinsic incentives. The mere presence of extrinsic incentives, such as money, may affect the attractiveness of intrinsic incentives in ways we would not be able to disentangle (see, e.g., [8, 9]). For example, once introduced with the option of receiving payment for installing the app, removing such payment may be perceived as a loss. Running three studies, where each participant saw exactly one type of incentive (with various levels), was our chosen approach to assure no contamination in terms of offerings. Except for the incentives, all three surveys had the exact same design.

Detailed in Appendix B, our surveys began by introducing the respondent to the idea of contact-tracing apps and how the conjoint analysis choice tasks worked. Respondents were then asked several questions, one of which was an attention question. Participants who did not pass this attention question were directed to the end of the study and their data were not used. At the end of the introductory stage, the importance of the research was restated, which has been shown in prior work to improve the validity of conjoint analysis results.

Next, respondents were shown a series of choice tasks. Each choice task depicted two app options, as well as a "None of these" option, as shown in Figure 5 in Appendix C. Since the study took place in the pandemic's early stage, when contact-tracing apps were not widely deployed yet, the choice task was entirely hypothetical. The series of choice tasks also included a "fixed task", which was an additional attention question. In this task, one of the two options was superior to the other on all features (e.g., maximum accuracy and does not drain the phone's battery). We excluded those who chose the least preferred option. If they chose "None" or if they chose the clearly-better option, they stayed in the survey.

Each app was described by seven attributes, with each attribute having several possible levels, as listed in Table 1. The attributes and levels in Table 1 give rise to a total of 960 (3 x 5 x 2 x 2 x 2 x 2 x 4) possible versions[1]. To reduce the number of versions, we used Sawtooth Software to create an orthogonalized design, which resulted in 300 possible versions, each with three conjoint tasks of two apps, and the one fixed attention check which we constructed manually.

At the end of the conjoint tasks, respondents completed a questionnaire that assessed their COVID-19-related knowledge using three questions (e.g., how long it takes for COVID-19-related symptoms to develop); their COVID-19-related experiences (e.g., whether they or someone they know has had COVID-19); their sociodemographics, such as whether they are a medical professional or essential worker, whether they are at high-risk for COVID-19, their health insurance status, and their level of Internet skill (measured using the Web-Use Skills Index [28]).

Survey Instrument Validation and Testing. Our survey instrument went through wording refinement and validation processes which included internal testing with colleagues, cognitive interviews in which participants did a cognitive walkthrough of the survey, and a pilot test with 18 participants. Moreover, we consulted with states and countries who were considering the various contact tracing apps designs.

3.2 Survey Sampling

About 1,800 respondents completed our surveys during June and July 2020, with 600 respondents completing each survey (intrinsic, healthcare, monetary), respectively[2]. Respondents were randomly assigned to one of the surveys. Respondents were recruited through the survey sampling firm Luc.id[3]. Respondents were compensated for their time in accordance with their agreement with the sample provider, and the mean

[1] All attributes levels were based on prior research (cited when applicable), on the various apps under development at the time of the research, and on discussions with various health authorities globally on their suggested levels of compensation in terms of monetary and health incentives.

[2] The sample size was determined according to a power analysis using the software for the conjoint analysis (Sawtooth) to ensure that the main effects standard errors in each condition were < 0.05 given the number of attributes, number of levels in each attribute and the number of choice tasks with which each user is presented.

[3] Information regarding the recruitment methodology and quality of Luc.id data can be found at https://luc.id/quality

Attribute	Description		Possible Values	
Accuracy	The accuracy of the app in identifying exposures to COVID-19		Detects [(1) 50; (2) 90; (3) 99] out of 100 exposures to coronavirus (wording from [36].)	
Incentives	Intrinsic	the individual or societal benefits of the app	Intrinsic	(1) Alert you if you have been exposed to someone who has coronavirus, without revealing your or their identity; (2) Reduce the number of people infected with coronavirus; (3) Inform you about locations near you which were recently visited by people infected with coronavirus, without revealing their identities; (4) Help researchers to get data about coronavirus without revealing your identity; (5) Contribute to the fight against coronavirus
	Monetary	a gift card given to downloading users	Monetary	(1) No gift card; [(2) $5; (3) $10; (4) $15; (5) $20] gift card to retailer of choice
	Healthcare	healthcare incentives	Healthcare	(1) No healthcare discount; (2) Any healthcare you need for a coronavirus infection will be free; (3) Your next three doctors visits for any condition will be free; (4) Your insurance premium for one month will be reimbursed; (5) Any coronavirus testing your doctor orders will be free
Mobile data	How much mobile data is used by the app		(1) Doesn't use mobile data; (2) Uses 300 MB (0.3GB) of your data plan every month	
Battery life	Affect of app on phone battery life		(1) Doesn't drain phone's battery; (2) Phone battery lasts 1 hour shorter than usual	
Information collected type	What data is collected about the user by the app		(1) Information about your location; (2) Information about who you have been near (within 6 feet)	
Info. storage location	Where the information collected by the app is stored		(1) Only on your device (2) Your data will be stored securely on the app provider's servers	
Possibly revealed information	What information about the user could possibly be leaked		Someone could: (1) learn that you've been exposed to coronavirus (2) learn who you have been near; (3) learn that you were infected with coronavirus; (4) know where you've been	

Table 1: Attributes presented in the conjoint analysis surveys

and median time for completing the task were 8.53 and 4.13 minutes, respectively. Quota sampling was used to ensure that respondents' demographics matched the census-reported demographics of the US as closely as possible with regard to age, gender, education level, income, ethnicity and geographic region. Respondents who incorrectly answered the attention check questions, or who did not have a mobile phone, were screened out of the survey. After screening out unqualified respondents, we were left with 490 participants for the intrinsic survey, 521 participants for the monetary survey, and 510 participants for the healthcare survey, total N = 490 + 521 + 510 = 1521 full responses. Demographics of the qualified participants for the three surveys are included in Table 2.

3.3 Analysis

3.3.1 Utilities and Importances Estimation

To explore how people weigh privacy relative to other adoption considerations (RQ1), we first estimate the utilities of each of the attributes' possible levels separately for each condition. We estimate the utilities via standard multinomial logit model, a common approach in conjoint analyses [26]. In such regression, we estimate a hierarchical model based on the choices people make in the series of choice tasks, and based on the relative preferences of others. Such analysis takes into account the repeated measure design and accounts for the multilevel (hierarchical) nature of conjoint experiments. The outcomes of the hierarchical model are the posterior draws of the individual utilities, from which we retain the individual posterior mean and standard deviation. Further details about the process of estimating the utilities are presented in Appendix A.

After estimating the individual part worth utilities for each of the app attributes, we compute the individual importance of each attribute. The importances of the attribute represent the extent to which the different attributes are meaningful to the respondents when considering whether to install the presented apps.

Zero-centered utilities were calculated for each individual. For each respondent a) each attribute's utilities sum to zero and, b) across attributes the differences between best and worst utilities are used to compute the importance of each attribute for each individual, and so the sum of the importances is 100%. To answer RQ1, we report the attributes' importances based on the *intrinsic* survey data.

		Intrinsic	Healthcare	Monetary
Age		μ=45.7 σ=16.6	μ=44.9 σ=16.8	μ=45.5 σ=17.5
Gender	Women	49.8%	51.6%	50.3%
	Men	49.6%	47.6%	49.3%
	Non-binary	0.4%	0.4%	0.2%
Ethnicity	White	69.6%	73.3%	73.1%
	Black	10.8%	10.2%	8.6%
	Hispanic	6.7%	4.3%	6.7%
	Asian	6.3%	4.3%	3.8%
	Nat. Am.	0.0%	0.0%	0.0%
Education	≤HS	29.4%	26.9%	25.9%
	Some Coll.	32.2%	34.1%	34.7%
	≥BS	38.2%	38.4%	39.0%
Income	≤$30K	25.3%	27.6%	26.3%
	$30-$50K	20.2%	19.8%	20.0%
	$50-$100K	31.2%	30.0%	32.2%
	$100-$200k	17.1%	17.5%	14.6%
	≥$200K	4.9%	3.5%	5.0%
Political aff.	Dem.	33.9%	36.5%	38.0%
	Rep.	34.5%	31.0%	30.7%
	Indep.	24.1%	23.9%	22.6%
	No pref.	7.6%	8.6%	8.6%

Table 2: Study demographics. Some demographic categories (gender, ethnicity, education, income) are not summed to 100% due to non-response.

3.3.2 Receptiveness Level

We define the participants' receptiveness level based on their intent to install any of the suggested apps. In each choice task, participants were able to choose one of the presented apps or none of them ("NONE: I wouldn't choose any of these"). Participants who always chose one of the suggested apps – i.e., did not choose "None" in any of the choice tasks – were categorized as *very receptive*. Alternatively, participants who chose "None" in *some* of the tasks, were categorized as *somewhat receptive*. A third group of participants includes those who chose "None" in all cases, and were categorized as *not receptive at all*. For analysis purposes, in all analyses where we examined questions related to the attributes' importance (RQ1, RQ2, RQ3(a,c)), we excluded the participants who would never install. When analyzing the overall receptiveness (RQ3b), we treated the "not receptive at all" as a group, separately from the group composed of those who were "somewhat receptive" and "very receptive".

3.4 Comparable Importances Estimation

In RQ2, we explore whether respondents' receptiveness level is associated with their attributes' prioritization. Since the surveys were not identical, as they differed in the incentive, we needed to create a common-ground first. To this end, we computed the relative importance of all other attributes [53]. We excluded the importance of the incentive attribute from each survey, and re-computed the relative importance of the remaining attributes. We term these importance values "comparable importance".

The comparable importance C of attribute a is computed as follows, where I represents the importance as explained in Section 3.3.1, A represents all the attributes *except* incentive, computed for each individual i, which we removed its subscript for simplicity.

$$C_a = \frac{I_{a'}}{\sum_{a'=1}^{A} I_{a'}}$$

Next, we used Scheirer-Ray-Hare and Wilcoxon tests to examine possible differences in attributes' comparable importance between receptiveness levels. The analyses were based on the entire data (we collapsed the conditions after excluding the incentive attribute). Per each attribute, we compared the comparable importances of the two explored groups (somewhat receptive vs. very receptive). The Scheirer-Ray-Hare test was used first to examine whether a difference between the attributes exists (analogous to the parametric MANOVA) and the Wilcoxon test was used as a post-hoc analysis to examine the difference between the groups per each attribute. We present the results' effect size using $r = z/\sqrt{n}$, where 0.1–0.3 reflects a small effect size, 0.3–0.5 reflects a medium effect size, and greater than 0.5 reflects a large effect size [51].

3.4.1 The Effect of Potential Adopters' Characteristics on Adoption Considerations

To answer RQ3c, and to explore the effect of respondents' characteristics (such as receptiveness level, demographics, and COVID-19 knowledge) and the incentives on their prioritization of attributes, we use linear regression analysis for each explored attribute.

3.5 Limitations

Self-report studies may not capture actual choices made in reality. However, prior work has found that conjoint analyses are good predictors of product choices [41, 55]. Additional work in the security and privacy domain finds that even if precise numeric estimates from self-report studies may not perfectly match real world behavior, the relative findings of such self-report studies well match measurements of real-world behavior [50].

This study is intended to test the relative importances of specific sets of attributes and to learn the varying importances of different incentives presented to potential COVID-19 contact-tracing adopters. Since it is not reasonable to conduct field studies which include all options presented in our series of conjoint studies, our conjoint estimates provide the results as close as possible to real-life decisions.

In conjoint analysis, comparison of attribute importance must be made with care. Choosing different levels for attributes might result in different utilities, which would result in different importances. For example, our choice of health incentives ranged from "No healthcare discount" to "Any coronavirus testing your doctor orders will be free". This was based on reasonable figures that were discussed with health officials of various states and countries as those considered when promoting the apps. However, a different range of gift-card or health benefits, for example very low and very high figures, may have resulted in different utilities for these attribute-levels, which would have made these attributes seem more important.

Finally, while we state that our method can beneficially be applied to other mHealth apps, obviously they can differ in many aspects. The proposed methodology may aid developers of mHealth apps in designing similar studies. The lessons learned from COVID-19 contact tracing apps about how people view different incentives may vary across time and contexts.

4 Results

4.1 The Role of Privacy in People's Adoption Considerations

Focusing on our explored case-study, COVID-19 contact tracing apps, we begin with exploring what is the role of privacy when people decide whether to install contact tracing apps (RQ1). To answer this question, we examine the importance of individual attributes when participants were presented with intrinsic incentives.

As shown in Figure 1, we found that privacy-related attributes were of low to medium importance relative to other attributes. The *risk of revealed information* was located as the fourth most important attribute – in the middle among the other attributes, with an importance of 12.38%. The two other privacy attributes, both related to the app architecture, *information storage location* and *collected information type*, were the least important attributes (8.86% and 7.39%, respectively). Of all attributes, the most important one was *accuracy*, with an importance of 29.44%. The two cost-related attributes – *mobile data* and *battery life* – were the second and the fifth most important attributes, respectively. We note that the second-most important attribute (mobile data) was approximately half as important as the most important attribute (accuracy) with an importance of 15.65%. Lastly, the intrinsic incentive attribute was the third most-important attribute (14.62%).

The differences between the importances of attributes were almost all significant, except for the difference between the attributes risk of revealed information and battery life. In terms of size of the difference between each two consecutive attributes, the effect size was large only for the difference between accuracy and mobile data (r = 0.51). For privacy-related attributes, the effect size was moderate for the differences between the risk of revealed information and the two architecture-related privacy attributes (the effect size of the difference between the risk of revealed information and information storage location was r = 0.31).The rest of the effects were considered small.

	Importance (%)		
Attribute	Intrinsic	Monetary	Healthcare
Accuracy	29.44	26.75	28.38
Incentive	14.62	28.22	26.16
Privacy	28.64	23.87	24.19
Costs	27.30	21.16	21.27

Table 3: Importance of the explored attributes per condition

Taking a more general perspective and to simplify our next analyses and discussion, we refer to the attributes in an aggregative perspective, as done by [21]. We aggregate cost-related and privacy-related attributes, leaving at first accuracy and incentive-related attributes separate, and later, when comparing across conditions, using the comparable importances without incentives which obviously differ.

4.2 The Effect of App Receptiveness Level on Attribute Importance

In answering RQ2, we sought to understand whether those who were somewhat or very receptive to installing the app (see Section 3.3.2) differed in how they weighed the explored attributes. In this and further analyses, in which we either collapse the conditions (current analysis) or compare observations across conditions (Section 4.3.3), we computed a *comparable importance* of the attributes per each condition, as explained in Section 3.4. Furthermore, in this and next analyses, we will mostly refer to the aggregated attributes (see Subsections 4.1): *privacy*, *costs*, and the solo attribute *accuracy* (as we excluded the incentive attribute, see Section 3.4).

As shown in Figure 2, we find that those who were very receptive to installing the app placed the most emphasis on the app's accuracy. Accuracy comprises 40.9% of intent-to-install among the most receptive respondents vs. 29.28% among those who are more undecided. Privacy and cost considerations had an opposite trend to accuracy: those who are more undecided placed more emphasis on these considerations than the very receptive participants. Scheirer-Ray-Hare test results pointed to differences between the attributes' importances across the receptiveness levels (Receptiveness level × Attribute: H = 290.867, $P < 0.001$, df = 2). Wilcoxon post-hoc analyses pointed to differences between the groups (somewhat receptive vs. very receptive) in all explored attributes. For the accuracy attribute, the difference had a moderate effect size (r = 0.36), while small effect sizes were found for privacy (r = 0.22) and costs (r = 0.23).

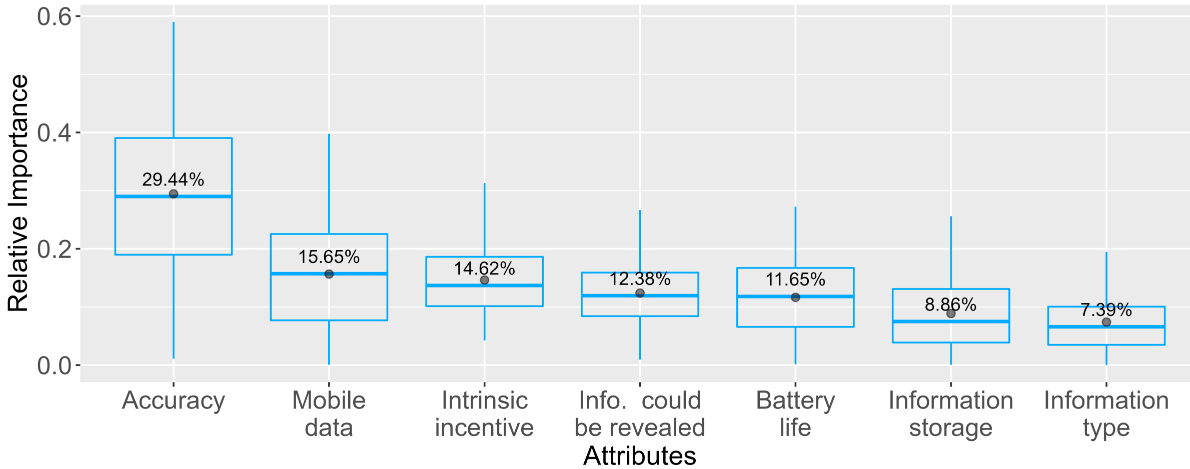

Figure 1: Attributes' importance when presented with intrinsic incentives.

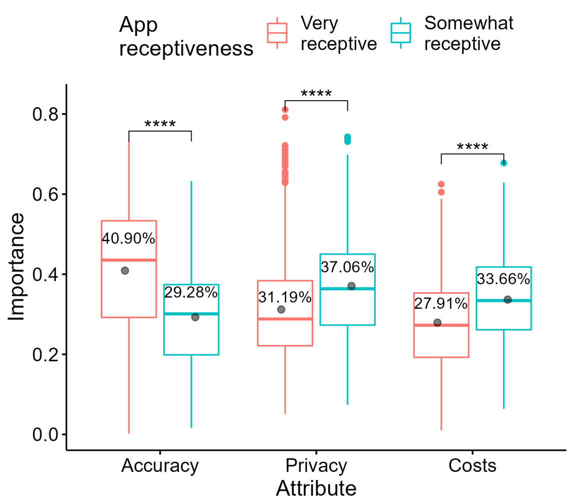

Figure 2: A comparison of the attributes comparable importances among different levels of app receptiveness.

4.3 The Role of Extrinsic Incentives in People's Adoption Considerations

4.3.1 The Role of Incentives Relative to Other Attributes

To explore how people prioritize extrinsic incentives relative to other adoption considerations (RQ3a), we examine the attributes' importances per condition, focusing on the observed trend. As shown in Table 3, we found that when extrinsic incentive were offered, they were considered as highly important. Incentives were considered least important when only intrinsic incentives were offered (14.62%), but were considered among the most important attributes when extrinisic incentives were offered (monetary: 28.22%; healthcare: 26.16%). In both extrinsic conditions, the difference between accuracy and the incentive was either non-significant (monetary) or significant with a small effect size (healthcare). We also examine privacy considerations per each condition. Relative to monetary incentive, privacy was significantly less important, with a moderate effect size (23.87% vs. 28.22%, $p < 0.001$, $r = 0.31$), whereas relative to healthcare incentive, the difference was significant, but had a small effect size (24.19% vs. 26.16%, $p = 0.002$, $r = 0.20$).

4.3.2 The Effect of Offering Extrinsic Incentives on Overall Willingness to Adopt

We first consider the relative impact of different levels of monetary incentives in the monetary-incentives condition. To do so, we explore the part-worth utilities of the different values offered: $0, $5, $10, $15 and $20. These part-worth utilities are directly related to the probability of adoption, as explained in Appendix A. Holding all else equal, each increase of the monetary incentives (from $0 to $5 to $10 and so on) significantly increases the likelihood of adoption. The utilities are presented in Figure 6, Appendix D, demonstrating significant differences between all consecutive levels, with a moderate or large effect size ($0 vs. $5, r = .706; $5 vs. $10, r = .471; $10 vs. $15, r = .503; and $15 vs. $20, r = .301.)

However, when we explore whether offering extrinsic incentives at all changes people's willingness to adopt the app (RQ3b), we find that they do not. We compare people's receptiveness to install the app across the conditions (see Section 3.3.2 for the measure's explanation) using a generalized linear model with binomial distribution. We considered those who were "very receptive" and "somewhat receptive" as *"receptive"* and those who were "not receptive at all" as *"not receptive"*. Presented in Table 5 in Appendix E, the regression analysis showed that none of the extrinsic incentives had a significant effect on the receptiveness level compared to the

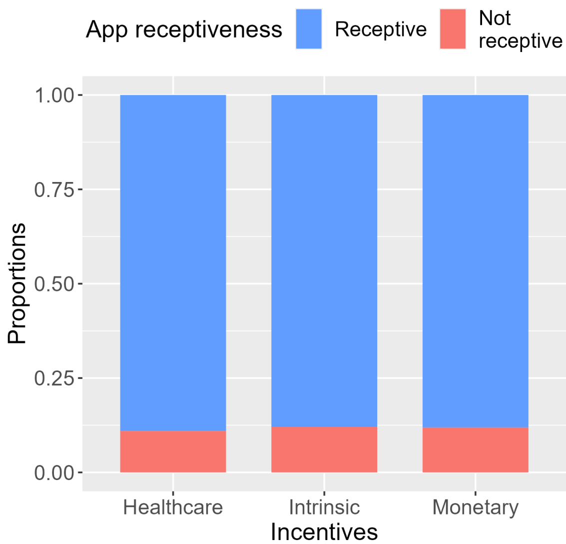

Figure 3: Receptiveness levels across conditions.

baseline intrinsic incentive (Null deviance: 1094.0 on 1520 df, Residual deviance: 1093.7 on 1518 df, AUC = 0.511). The regression analysis results support our exploration of the two receptiveness levels' distributions across conditions. Presented in Figure 3 and in Table 6 in Appendix F, we see that the receptiveness levels are distributed similarly across conditions, in which approximately 88% of participants were receptive to install the app, and 12% of participants were not receptive at all.

4.3.3 Adoption Considerations Under Extrinsic Incentives and Receptiveness Levels

In RQ3c, we explore the effect of offering extrinsic incentives on installation considerations among different consumers, differing, for example, in their app receptiveness. To answer this question, we used linear regression analysis to explore how the attributes' comparable importances are affected by the explored variables. We conducted a two-step analysis, in which the first analysis included only independent variables that assess main effects (Table 4), and the second analysis included an interaction term [11]. The main effect variables included incentive offered, receptiveness level, demographics, and COVID-19-related questions, such as the participants' knowledge related to COVID-19 (see Appendix B for survey questions). The second step analysis explored the effect of the interaction between incentive offered and receptiveness level on the attributes' comparable importances (Table 7).

Examining the main effect of the explored variables, we found that receptiveness level had the greatest effect on the attributes' comparable importance. The results echo our results for RQ2, showing that participants who were somewhat receptive to installing the contact tracing apps considered the accuracy attribute as less important than those who were very receptive (the regression's baseline level) (β= -0.12, $p < 0.001$). A smaller and opposite effect was observed for privacy and costs (privacy: β= 0.06; costs: β= 0.06; $p < 0.001$).

Size-wise, an equal effect was observed for the explored interaction effect. Demonstrated in Figure 4, we observed that the interaction effect of somewhat receptive × healthcare incentive was significant for both privacy and accuracy, but not costs. Among those who were somewhat receptive, privacy was of higher importance for those who were offered healthcare incentives than those who were offered intrinsic incentives. However, for those who were very receptive, conducting the same comparison (intrinsic vs. healthcare), we see privacy has lower importance for those who were offered healthcare incentives (β= 0.10, $p < 0.001$). We note here that when we explored each attribute separately (i.e., without aggregating attributes of the same topic), most of the observed effect was due to the risk of revealed information attribute. Examining accuracy, those who were somewhat receptive and were offered the healthcare incentive considered accuracy to be less important than those who were presented with the intrinsic incentive. However, for those who were very receptive and were offered the healthcare incentive, the opposite was observed; they considered accuracy as more important than those presented with the intrinsic incentive.

When examining the interaction effect of somewhat receptive × monetary incentive, similar but weaker effect was observed in terms of accuracy (β= -0.06, $p = 0.005$). Unlike the healthcare incentive, however, the interaction effect on privacy when offered the monetary incentive was non-signficant. For the costs attribute, the interaction effects were non-significant for both the healthcare and monetary incentives.

Summarizing the interaction effect results, we observed different effects among different attributes and different effects between the incentives offered. First, significant effects were observed only for accuracy and privacy. Second, we see that the healthcare incentive resulted in a greater differentiation between the receptiveness levels than the monetary incentive. This phenomenon is especially noticeable in the case of privacy, in which the effect was relatively strong for healthcare, and was non-significant for monetary.

Other explored main effects were either relatively weak (with estimated coefficient of 0.04 or less) or non-significant. Both direct incentives had a similar effect on the attributes' comparable importance, showing that those who were offered direct incentives significantly considered 1) accuracy as more important and 2) costs as less important than those who were presented with intrinsic incentive (the regression baseline level) (for example, healthcare - accuracy: β= 0.04, costs: β= -0.03, $p < 0.001$).

Examining demographics and personal COVID-related variables, we found varying results among different factors and attributes. Gender had a small effect on costs, with women considering it as more important than men (β= 0.02, p =

	Attributes		
	Accuracy	Privacy	Costs
Constant	**0.34*** (0.32, 0.37)**	**0.34*** (0.31, 0.36)**	**0.32*** (0.30, 0.34)**
Receptiveness: Somewhat	**−0.12*** (−0.14, −0.11)**	**0.06*** (0.05, 0.08)**	**0.06*** (0.04, 0.07)**
Condition: Healthcare	**0.04*** (0.02, 0.06)**	−0.01 (−0.03, 0.003)	**−0.03*** (−0.04, −0.02)**
Condition: Monetary	**0.04*** (0.02, 0.05)**	−0.01 (−0.02, 0.01)	**−0.03** (−0.04, −0.01)**
Age	−0.01 (−0.03, 0.001)	0.002 (−0.01, 0.02)	0.01 (−0.0003, 0.03)
Gender: Woman	−0.004 (−0.02, 0.01)	−0.01 (−0.02, −0.0000)	**0.02* (0.004, 0.03)**
Ethnicity: Black	−0.01 (−0.04, 0.01)	0.02 (−0.002, 0.04)	−0.005 (−0.02, 0.02)
Ethnicity: Hispanic	−0.01 (−0.04, 0.01)	0.02 (−0.01, 0.04)	−0.005 (−0.03, 0.02)
Ethnicity: Asian	0.02 (−0.01, 0.05)	−0.01 (−0.04, 0.01)	−0.01 (−0.03, 0.02)
Edu. High school or less	0.01 (−0.01, 0.03)	**−0.02* (−0.04, −0.01)**	0.01 (−0.01, 0.03)
Edu. Some college	0.01 (−0.01, 0.03)	0.001 (−0.01, 0.02)	−0.01 (−0.02, 0.01)
Income (log)	0.002 (−0.01, 0.02)	0.001 (−0.01, 0.01)	−0.003 (−0.02, 0.01)
Opinion: Democrat	0.01 (−0.01, 0.02)	0.001 (−0.01, 0.01)	−0.01 (−0.02, 0.002)
Internet Skills	−0.01 (−0.03, 0.004)	0.01 (0.001, 0.03)	−0.003 (−0.02, 0.01)
Has health insurance	−0.01 (−0.03, 0.02)	0.01 (−0.01, 0.03)	−0.003 (−0.02, 0.02)
COVID: Death	**−0.02* (−0.04, −0.004)**	**0.02* (0.004, 0.04)**	0.002 (−0.01, 0.02)
Is an essential worker	−0.003 (−0.02, 0.01)	0.0002 (−0.01, 0.01)	0.003 (−0.01, 0.02)
COVID: News	−0.002 (−0.02, 0.01)	−0.01 (−0.02, 0.004)	0.01 (−0.001, 0.02)
COVID: Knowledge	**0.03*** (0.02, 0.05)**	**−0.02* (−0.03, −0.01)**	−0.01 (−0.03, −0.002)
Interaction effect regression†			
Receptiveness: Somewhat × Condition: Healthcare	**−0.12*** (−0.16, −0.09)**	**0.10*** (0.07, 0.13)**	0.02 (−0.01, 0.05)
Receptiveness: Somewhat × Condition: Monetary	**−0.06** (−0.10, −0.02)**	0.03 (−0.002, 0.06)	0.03 (0.002, 0.06)
Observations	1,270	1,270	1,270
R^2	0.15	0.07	0.07
Adjusted R^2	0.14	0.06	0.06
Residual Std. Error (df = 1251)	0.15	0.12	0.12
F Statistic (df = 18; 1251)	12.44***	5.60***	5.59***
Note:			*p<0.05; **p<0.01; ***p<0.001

Table 4: Standardized Multivariate Multiple Regression. †See Table 7 for regression analysis that includes interaction effects.

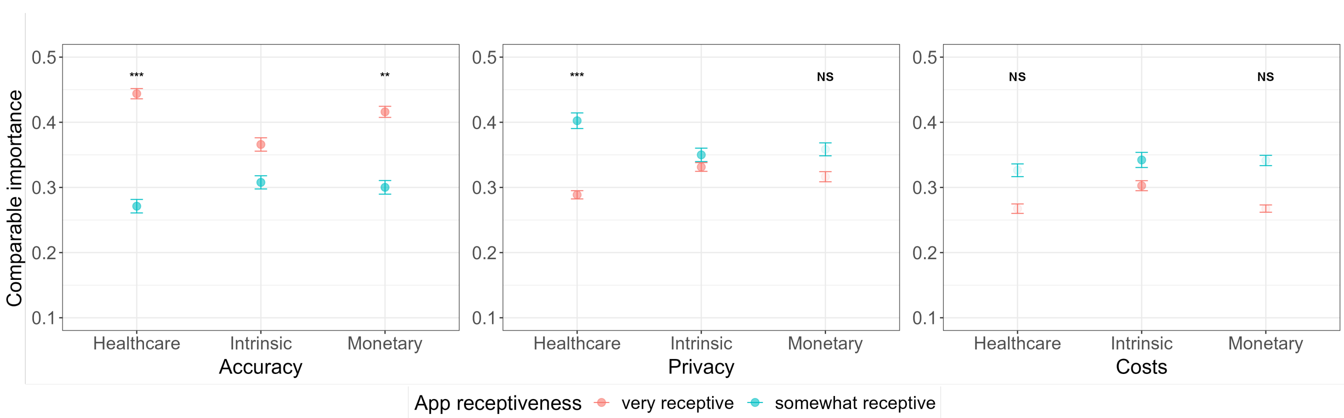

Figure 4: Interaction effect between incentive offered and receptiveness level on attribute's comparable importance. NS/* indicates (non)significance of difference for external (Healthcare and Monetary) vs. Intrinsic incentive conditions.

0.028). Education affected privacy considerations, showing that those who had an education level of high school or less considered privacy as less important than those who had a Bachelor's degree or above (β= -0.02, p = 0.037). Two COVID-related questions had a significant effect on privacy and accuracy attributes' comparable importance: participants who personally knew someone who died from the disease considered privacy as more important, but considered accuracy as less important than others (privacy: β= 0.02, p = 0.035; accuracy: β= -0.02, p = 0.047). Participants who had a greater knowledge about COVID-19 considered privacy as less important, but considered accuracy as more important (privacy: β= -0.02, p = 0.016; accuracy: β= 0.03, p < 0.001).

5 Discussion

This work aimed to investigate the adoption considerations of privacy-sensitive apps in the health domain. As a case-study, we explored the adoption of COVID-19 contact-tracing apps. From a research perspective, the pandemic allowed us to explore new technologies, to ask questions about people's perceptions and behavior, and to witness the implications as they were happening. Therefore, exploring these apps as a case study for future lessons is highly valuable.

Specifically, in our study we explored how potential adopters prioritize privacy relative to other adoption considerations (RQ1), and how their prioritization differed based on the user's receptiveness to installing the app (RQ2) and the presence of extrinsic incentives (RQ3). To this end, we used a randomized conjoint analysis study with participants from the U.S. approximately four months after the COVID-19 pandemic started.

We find that for (RQ1), when intrinsic incentives are presented, people consider privacy, accuracy and costs considerations similarly, standing as the three most important considerations, and consider the incentive itself as the least important attribute. We note here, however, that both privacy and costs considerations consist of more than one attribute, while accuracy has a similar importance, but as a single attribute. Further, we find that for (RQ2) those who are very receptive to adoption of COVID-19 apps place more importance on the accuracy of the app (i.e., whether it is effective), while those who are only somewhat receptive place more emphasis on the app's privacy and costs (of note, in this analysis we did not compare the effect of incentives, and computed the comparable importances across conditions). In other words, for those who were hesitant to install the apps, their main hesitancy was in regards to privacy considerations and costs such as battery and data usage. However, if they were already willing to install the app, accuracy was the most important factor. This is an important mechanism, especially when the intent is to encourage adoption. If the desire is to attract the hesitants, more emphasis should be placed on privacy and cost considerations.

Compared to intrinsic incentives, when presented with extrinsic incentives (RQ3a) – either a monetary gift card or healthcare – participants' importances were placed differently: the extrinsic incentives were placed as important as accuracy. Privacy and costs considerations became the least important attributes under these conditions. Further, we find that for (RQ3b) offering extrinsic incentives did not affect participants' overall intent to adopt the apps. This has important implications for policy makers and app promoters who may consider offering extrinsic incentives. These did not affect people's intent to adopt, but rather only their choice of specific app. Finally, we find that for (RQ3c) the two factors – extrinsic incentives and receptiveness level – sometimes interact, suggesting that different incentives may have a heterogeneous effect depending on a potential user's receptiveness to COVID-19 apps in general.

In what follows, we place our results in the context of prior work, synthesizing takeaways for the design of future mHealth technologies. We conclude with generalizations of our methodology for exploring similar questions in the future.

5.1 Implications for Design & Promotion of Privacy-Sensitive Health Technologies

Privacy Considerations. The least important attributes in our study were two privacy-related attributes: the collected data (location vs. proximity data) and the information storage location (centralized vs. decentralized). Instead, participants cared more about the possible information that might be leaked as a result of using the app. This observation might be explained by the previously documented differences in people's social and institutional privacy concerns [47], in which socially-relevant data protections (e.g., potential leakage of information about social contacts) may be more salient than institutionally-related protections (location of data storage) [4]. The conclusions from our findings are not to abandon privacy-preserving architectures. Rather, our conclusions shed light on what portions of these architectures are most salient to *market*: those that have the most social relevance.

The Power of Accuracy. Prior work has shown that app accuracy is positively associated with people's intent to adopt [21, 36]. In our study, accuracy was considered among the most important attributes regardless of whether intrinsic and extrinsic incentives were offered. We find that people consider accuracy one of the most important adoption considerations, even more so than privacy. Yet, little research was done to measure accuracy prior to or even during COVID app deployment [25, 61]. Combined with prior work in the COVID-19 setting which found that people's adoption intent can be predicted based on false-negative and false-positive rates of contact tracing apps [36], these results underscore the importance of future work studying privacy-accuracy tradeoffs in order to ensure the adoption potential of new applications.

Studying such tradeoffs is relevant far beyond the COVID-

19 setting. mHealth data in general is viewed as particularly sensitive [33], and thus there are increasing calls to use a variety of privacy-protective approaches such as differential privacy to protect data collected by mHealth applications [37,54]. Just like the tradeoffs of decentralized contact tracing architectures, protective approaches like differential privacy necessitate tradeoffs between privacy and the utility of the collected data for both the user of the mHealth apps and researchers who may seek to conduct medical research on that data.

Offering incentives. Our study randomized the incentive types that people were presented with. This unique study design allows us to explore additional effects of offering incentives on adoption considerations, relative to prior work explorations.

Referring to the extrinsic incentives surveys as "stand alone" studies, we compare our results to those found in prior choice-based studies, focusing on Jonker et al. [35] and Frimpong and Helleringer [21]. Our results support these studies, finding that the extrinsic incentives offered, both monetary and healthcare, were among the most important attributes. On the other hand, when intrinsic incentives were presented in our study, they were much less important than the most important attribute, accuracy, approximately by half. This result has implication for promoting efforts, suggesting that if extrinsic incentives are not used as a means to increase adoption, communication efforts should center on attributes other than intrinsic incentives, such as on the app's accuracy.

Examining all surveys results at once, however, we found that the overall intent to adopt, as it was measured by the proportion of those deciding not to select any of the suggested apps, was similar across conditions. We term this group as "not receptive", and in our study, approximately 12% of respondents belonged to this group. Similar result was observed by Frimpong and Helleringer [21] (U.S sample, 10%), and higher proportion by Jonker et al. [35] (Netherlands sample, 25%). This result provides an additional perspective, in which when explored separately, extrinsic incentives are observed as playing a significant role in people's adoption considerations. However, when extrinsic incentives are examined relative to intrinsic incentives in a randomized control trial and without the participants aware that the other option is available – we do not find an effect on the overall intent to adopt.

Our observed non-significant effect of extrinsic incentives on intent to adopt contradicts prior field studies results. Conducted in Germany, the studies of Munzert et al. [43] and Fast and Schnurr [17] showed that offering monetary incentives increased the app's installation. One possible explanation for this difference might be due to the explanation about the app's characteristics presented to our participants versus those in previous studies. The exact information about the app provided to the participants is not given in Fast and Schnurr [17] and Munzert et al. [43], but a reasonable assumption would be that participants were not presented with information about specific attributes and detailed possible related risks. Therefore, in such a field study context, the comparison is between a general contact tracing app – with or without getting paid for installing it. In such a situation, the attention given to the offered money might be greater than it was in our study context, in which the extrinsic incentive was only one attribute out of seven. Thus, the differences found between our study and these field studies raise questions about the transparency regarding technologies' characteristics in real-world situations.

The outcome of incentivizing people to participate in a desired behavior has been widely explored in different contexts, such as education, pro-social behavior, and maintaining a timeline (e.g., [23]). For pro-social behavior, there is an ongoing debate about using extrinsic incentives to increase participation in such behavior, both from an ethical perspective [52] and actual outcome [20], that is, whether it promotes the desired behavior. Our findings, in which extrinsic incentives did not increase participants' intent to adopt, suggest that in the context of contact-tracing apps, another approach is preferred. For example, we observed that accuracy was as important in the decision to adopt the apps as extrinsic incentives. This finding suggests that a possible direction would be to put more efforts and money on improving the performance of these apps as a whole, instead of using these efforts to incentivize people to adopt.

While field studies have the clear advantage of being closer to reality than scenario-based studies, the later are also of great valuable implications. Conjoint analysis studies are widely used in marketing research and are useful in providing estimations about consumer preferences even before a product is launched. Our conjoint analysis with an additional layer of randomization assures participants will not be exposed to multiple options that may create reference dependencies [2,27,55]. Simulation studies are easier and less expensive to conduct, and allows researchers to explore many variations at once, as with the current study. An equivalent study would not have been possible as a field study, as it would have required the development of multiple apps. At the same time, however, participants were only asked to report on their expected behavior, and not to actually make a choice. These limitations should be considered when designing future studies.

Differences in receptiveness to install. Across all conditions, ~60% of the participants were very receptive to installing the suggested contact-tracing apps and ~28% were somewhat receptive. The remaining ~12% of the participants were not receptive at all to installing the app, similar to Geber and Friemel's results [22]. Based on their exploration of people's intention and actual adoption of Switzerland's contact-tracing app, Geber and Friemel suggest that communication efforts to increase adoption should focus on those who are willing to adopt the app at least to some extent (equivalent to those who are "very" or "somewhat" receptive in our study). Our study provides novel insights into how to decide what to emphasize in those communications. In our study context, we found that those who were most receptive to install the app considered accuracy significantly more important than those who were more hesitant to adopt it. On the contrary, those who were hesitant placed greater emphasis on privacy and cost considerations. In encouraging future mHealth technologies, such segmentation could be applied to determine preferences among those who differ in their hesitancy to adopt. Accordingly, a customized message could be targeted to groups of people based on their receptiveness level.

Adding to previous works on adoption considerations, who either explored extrinsic incentives [17,21,32,35,43] or types of potential adopters [22], our study explores the interaction of these factors. Our findings, as detailed in Section 4.3.3, show that different extrinsic incentives have a different effect on people with various levels of receptiveness to installing the app. For example, those who were hesitant about installing the app *and* were offered with healthcare incentives found privacy more important than those who were presented with intrinsic incentives. On the other hand, the opposite trend was observed for the most receptive participants. As noted in Section 4.3.3, most of this effect stemmed from people's concerns about their information being revealed to other people ("someone"). These results suggest that those who hesitate to install are perhaps more concerned about their social privacy, but this depends on the context [45], whether the incentive is health-related or not (i.e., merely money). Possibly, people were concerned about data that might be collected in exchange for the suggested health-related benefit, thereby increasing the risk that it will be exposed unintentionally to others.

5.2 Conclusions

Overall, our study design allows us to explore the considerations people have prior to installing contact tracing apps. This design and some of the outcomes can be generalized to other mobile health apps, most of which share similar traits of the need for accuracy, data protection, costs and incentives. Extrinsic incentives may not increase the overall intent to adopt, but they do change the emphasis people place on different aspects of the products. This can assist in both resource allocation in product design and in marketing messages. Moreover, the results suggest that those who are most receptive to installing the apps place more emphasis on accuracy, whereas those who are hesitant are more concerned about the privacy of the app. The randomized trial allowed us to disentangle and cleanly detect the role of incentives in affecting the willingness to adopt. This design can be tuned for other specific mHealth apps and potential incentives to be offered. As discussed in the limitations, however, our study is not a field study and participants were not actively installing the app. However, with the ability to randomize all of the app features and messages, and with the inability to run so many variations of such study in the field without possible interference between conditions, our methodology offers a useful way to analyze people's perceptions and choice considerations.

In his work, Istepanian discusses the great impact COVID has had on investments in digital health technologies that go beyond contact tracing apps, such as remote patient monitoring and disease diagnosis [34]. While our work was conducted in the context of COVID-19 contact-tracing apps, several of our results offer hypotheses and insights relevant to other privacy-sensitive health applications, as well. First, the lessons learned in our study on tensions between privacy, accuracy, and incentives offer hypotheses to test during feature prioritisation in other health apps such as diabetes management apps [12] , where offering incentives has been previously explored as a means to increase adoption. Further, contact-tracing interventions are used not only for COVID but for the other infectious diseases, such as tuberculosis and HIV [31], and future exploration of digital contact-tracing for these and other diseases is necessary [15]. Thus, the high external validity present during the early period of the pandemic offers a rare, realistic lens into people's decision-making when faced with a stressful, medically- and privacy-sensitive decision.

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A Detailed Explanation of Utilities Estimation

To explore how people weigh the different app attributes in their adoption considerations, we first estimate the utilities of each of the attributes' possible levels, for each condition separately.

We estimate the utilities via standard multinomial logit model: let U_{ijt} denote participant i's indirect utility for alternative (contact tracing app) $j \in \{1, 2, \text{None option}\}$ on choice occasion $t \in \{1, 2, 3\}$. We assume (the standard assumption) that indirect utility can be expressed as a linear function of the alternative's attributes, X_{jt}. The utility of product j in choice task t for user i is therefore:

$$U_{ijt} = \beta_i \cdot X_{jt} + \varepsilon_{ijt}$$

where β_i is the part-worth utilities of participant i, X_{jt} is a binary vector representing alternative j's attributes, and is of length $\sum_{a=1}^{7} L_a$. In our case we have 7 attributes, and L_a, the number of levels for attribute a, varies from 2 to 5, with a total of 22 attribute levels altogether. See Table 1. Finally, ε_{ijt} is the error term – assumed IID according to a Type I Extreme Value distribution.

Estimating a hierarchical model, we let customers' β_i be drawn from:

$$\beta_i \sim \text{MVN}(\Theta, \Sigma)$$

where Θ is the mean utility across the population, and Σ is the covariance matrix constructed from a correlation matrix Ω and a diagonal variance τ.

Customer i would choose contact tracing app j at choice task t with probability following a multinomial logit specification:

$$\Pr(y_{it} = j) = \frac{e^{U_{ijt}}}{\sum\limits_{all\, j'} e^{U_{ij't}}}$$

In other words: Customer i would be more likely to choose contact tracing app j if a higher utility relative to the other options in this choice task t. The above probability notation is articulating this assumption. The parameters are estimated using Sawtooth's built in Hierarchical Bayesian framework. The outcomes of the hierarchical model are the posterior draws of the individual utilities, from which we retain the individual posterior mean and standard deviation of the utilities of each attribute level.

B Experiment Questions

1. Introduction: Imagine that there is a mobile phone app intended to help combat the coronavirus in the U.S. Different apps have different benefits and risks and may collect different types of information on you.
   In this survey, you will see a series of choice tasks. In each choice task, please choose carefully, as if you were considering downloading the coronavirus tracking app.
   Throughout the study, you will be asked comprehension questions that will verify your attention and understanding of the process of the study. If you do not answer these questions correctly, you will be withdrawn from the study, and will not be eligible for payment.
2. Qualification question: Do you have a mobile phone with access to the internet? [Yes, No, No answer]
3. Attention check: Please think of the near future - after state limitations will be lifted.
   It is important that you pay attention to this survey. Please check greatly positive below. [Greatly negative, Very negative, Somewhat negative, No change, Somewhat positive, Very positive, Greatly positive]
4. Pre-experiment: Your responses in this survey will help to inform U.S. policy and scientific research and app development related to the spread of coronavirus. Please make sure to choose the option that best reflects your likelihood of downloading a coronavirus tracking app.
5. Asking the participants to choose one of the options (or none of them): Please look carefully at the options below. Each column represents an app with different attributes that will be designed and distributed by a health protection agency. Assume both apps are equally popular. Which one would you choose?
   (The participants were presented with two optional apps to choose from, and also the option not choose any of them. See Figure 5 for an example.)
6. COVID-related questions
   (a) How closely, if at all, have you been following news about the outbreak of the Coronavirus also known as COVID-19? [Not at all closely, Not too closely, Somewhat closely, Very closely]
   (b) Below are some questions about the Coronavirus (COVID-19). Please select the correct answer to these questions. If you don't know the correct answer, take your best guess.
      i. How long does it take between catching Coronavirus and beginning to have symptoms? [A few minutes, One day, Up to one week, Up to two weeks]
      ii. What can be said about people who have tested positive for Coronavirus but are in good health? [They are not contagious until they show clear symptoms, They are definitely going to show symptoms within a few days, They are contagious regardless of whether they show symptoms, They are already immunized and can go out in public]
      iii. Which of the following is true about the Coronavirus in the United States in the 2019-2020 season? [It has killed fewer people than the regular flu this year, It has killed about the same number of people as the regular flu this year, It has killed more people than the regular flu this year]
   (c) Did you do an online search (such as using Google) to help answer the questions we just asked you? [Yes, for one of them; Yes, for some of them; Yes, for all of them; No, I did not search for answers, but found them hard to answer; No, I did not search for answers and found them easy to answer]
   (d) Have you been diagnosed with the Coronavirus (COVID-19)? [yes, no]
   (e) Do you know any people who have been diagnosed with Coronavirus (COVID-19)? [yes, no]
   (f) Has anyone you know died from the disease? [yes, no]
   (g) Do you have a degree in a medical profession such as medicine, nursing or pharmacy? [yes, no]
   (h) Do you or anyone in your household currently work at a healthcare facility, or visit a healthcare facility for work reasons, where Coronavirus (COVID-19) patients are cared for? [yes, no]
   (i) Are you an essential employee who is currently required to leave your house to work? [yes, no]
   (j) Do you have any of the following medical conditions? Check all that apply. [High blood pressure; Diabetes; Cardiovascular disease, heart disease; Chronic respiratory disease, lung disease (such as asthma, COPD); Cancer; Conditions and therapies that weaken the immune system; I take immunosuppressive medication; Severe obesity (body mass index [BMI] of 40 or higher); I am pregnant; None of the above]

C Conjoint Choice Task Example

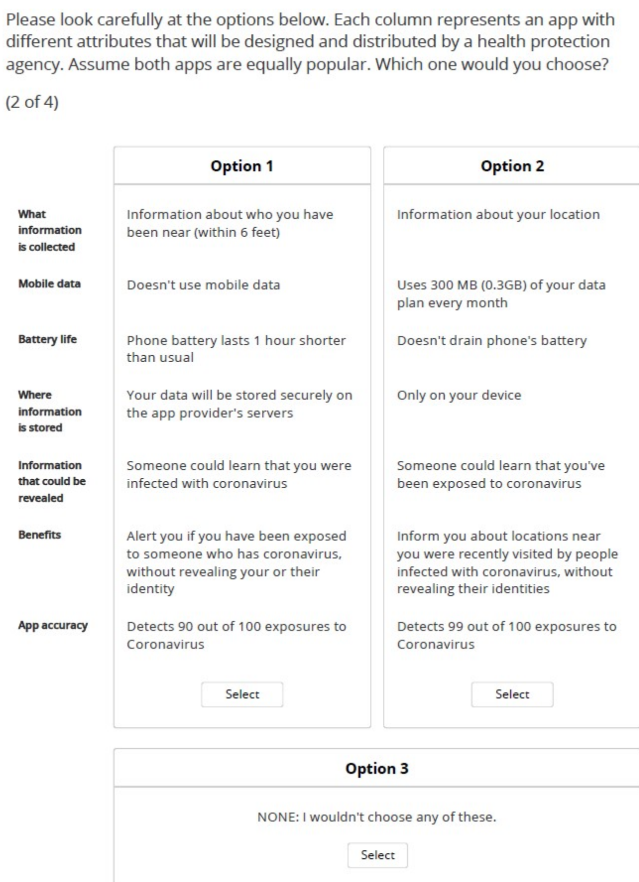

Figure 5: Conjoint choice task between app pairs.

D Gift cards utilities

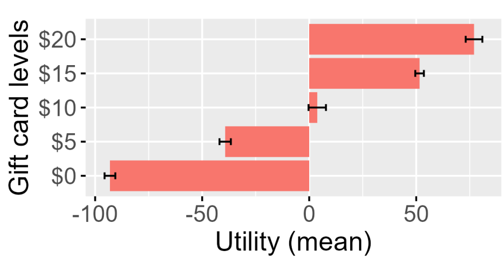

Figure 6: The mean utilities of the gift cards levels. Error bars present the 95% confidence interval

E Regression Analysis – comparing receptiveness levels across conditions

	Estimated Coefficient	Std. Error	z value	P value
(Intercept)	2.093	0.142	14.776	<0.001
Monetary	-0.091	0.196	-0.464	0.643
Intrinsic	-0.104	0.198	-0.525	0.599

Table 5: Comparing app receptiveness across conditions using generalized linear model with binomial distribution. Null deviance: 1094.0 on 1520 df, Residual deviance: 1093.7 on 1518 df, AUC = 0.511.

F Receptiveness Levels Groups Across the Incentives Conditions

	Intrinsic	Healthcare	Monetary
Very receptive	295 (60.2%)	304 (59.7%)	298 (57.2%)
Somewhat receptive	136 (27.8%)	150 (29.4%)	161 (30.9%)
Not receptive at all	59 (12%)	56 (10.9%)	62 (11.9%)
Total	490 (100%)	510 (100%)	521 (100%)

Table 6: Number of respondents per each condition based on their receptiveness level, and their proportion relative to each condition's total sample.

G Regression Analysis – including interaction effect

	Attributes		
	Accuracy	Privacy	Costs
Constant	**0.34*** (0.32, 0.37)**	**0.34*** (0.31, 0.36)**	**0.32*** (0.30, 0.34)**
Receptiveness: Somewhat	**−0.06*** (−0.08, −0.03)**	0.02 (−0.003, 0.04)	**0.04** (0.02, 0.06)**
Condition: Healthcare	**0.04*** (0.02, 0.06)**	−0.01 (−0.02, 0.004)	**−0.03*** (−0.04, −0.01)**
Condition: Monetary	**0.03*** (0.02, 0.05)**	−0.01 (−0.02, 0.01)	**−0.03** (−0.04, −0.01)**
Age	−0.02 (−0.03, 0.0000)	0.003 (−0.01, 0.02)	0.01 (−0.0004, 0.03)
Gender: Woman	−0.01 (−0.02, 0.01)	−0.01 (−0.02, 0.001)	**0.02* (0.004, 0.03)**
Ethnicity: Black	−0.01 (−0.04, 0.01)	0.02 (−0.003, 0.04)	−0.01 (−0.03, 0.01)
Ethnicity: Hispanic	−0.01 (−0.04, 0.02)	0.02 (−0.01, 0.04)	−0.004 (−0.03, 0.02)
Ethnicity: Asian	0.02 (−0.01, 0.05)	−0.01 (−0.04, 0.01)	−0.01 (−0.03, 0.02)
Edu. High school or less	0.01 (−0.01, 0.03)	**−0.02* (−0.04, −0.005)**	0.01 (−0.01, 0.03)
Edu. Some college	0.01 (−0.01, 0.03)	−0.001 (−0.02, 0.01)	−0.01 (−0.02, 0.01)
Income (log)	0.002 (−0.01, 0.02)	0.001 (−0.01, 0.01)	−0.003 (−0.02, 0.01)
Opinion: Democrat	0.01 (−0.01, 0.02)	0.004 (−0.01, 0.02)	−0.01 (−0.02, 0.002)
Internet Skills	−0.01 (−0.03, 0.003)	0.01 (0.002, 0.03)	−0.003 (−0.01, 0.01)
Has health insurance	−0.005 (−0.03, 0.02)	0.01 (−0.01, 0.03)	−0.003 (−0.02, 0.02)
COVID: Death	−0.02 (−0.04, −0.003)	**0.02* (0.004, 0.04)**	0.002 (−0.01, 0.02)
Is an essential worker	−0.002 (−0.02, 0.01)	−0.0005 (−0.01, 0.01)	0.002 (−0.01, 0.02)
COVID: News	−0.001 (−0.02, 0.01)	−0.01 (−0.02, 0.003)	0.01 (−0.002, 0.02)
COVID: Knowledge	**0.04*** (0.02, 0.05)**	**−0.02** (−0.04, −0.01)**	**−0.01* (−0.03, −0.002)**
Receptiveness: Somewhat * Condition: Healthcare	**−0.12*** (−0.16, −0.09)**	**0.10*** (0.07, 0.13)**	0.02 (−0.01, 0.05)
Receptiveness: Somewhat * Condition: Monetary	**−0.06** (−0.10, −0.02)**	0.03 (−0.002, 0.06)	0.03 (0.002, 0.06)
Observations	1,270	1,270	1,270
R^2	0.17	0.10	0.08
Adjusted R^2	0.16	0.08	0.06
Residual Std. Error (df = 1249)	0.14	0.12	0.12
F Statistic (df = 20; 1249)	13.05***	6.79***	5.19***
Note:			*p<0.05; **p<0.01; ***p<0.001

Table 7: Standardized Multivariate Multiple Regression, including interaction term.