Unpacking Intention and Behavior: Explaining Contact Tracing App Adoption and Hesitancy in the United States

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ABSTRACT

COVID-19 has demonstrated the importance of digital contact tracing apps in reducing the spread of disease. Despite people widely expressing interest in using contact tracing apps, actual installation rates have been low in many parts of the world. Prior studies suggest that decisions to use these apps are largely shaped by pandemic beliefs, social influences, perceived benefits and harms, and other factors. However, there is a gap in understanding what factors motivate intention, but not subsequent behavior of actual adoption. Reporting on a survey of 290 U.S. residents, we disentangle the intention-behavior gap by investigating factors associated with installing a contact tracing app from those associated with intending to install, but not actually installing. Our results suggest that social norms can be leveraged to span the intention-behavior gap, and that a privacy paradox may influence people's adoption decisions. We present recommendations for technologies that enlist individuals to address collective challenges.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**; • **Applied computing → Health informatics**.

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1 INTRODUCTION

Contact tracing has been described as one of three pillars for controlling the spread of the COVID-19 pandemic, alongside case isolation and physical distancing [53]. Technology has emerged as a prominent strategy for implementing contact tracing, with many countries and regions developing and releasing government-sponsored mobile apps. Generally, digital contact tracing apps work by sending a notification when one has been in physical proximity with an infected person, usually recommending that one gets tested for COVID-19. Particularly early in the COVID-19 pandemic, interest in contact tracing technology and optimism for the solution was high. Early survey research in Europe, the UK, and the United States found that 74.8% of respondents said they would probably or definitely install a contact tracing app if one were available [e.g., 6]. Other research suggested that if 56% of the population used a digital contact tracing app, it would be sufficient to suppress the spread of the pandemic [41], which has led most governments and health agencies to target 60% adoption. However, this goal has generally not been met in regions where contact tracing apps are optional, such as the U.S. (Approximately 14% adoption [22]), Europe (Average 20% adoption across European countries [8]), and India (10-15% [94]).

In order to design and deploy technologies to address global challenges, it is important to understand what factors influence people to use those technologies effectively. One explanation for the high levels of interest, but low levels of adoption of contact tracing technology is there exists an intention-behavior gap. Intention-behavior gaps investigate cases where people express intention to act, but do not follow through to carry out actions based on that intention [77]. If technologies are designed to suit factors related to stated intentions, without an understanding of how those map to actual behavior, it can result in the following problems. First, adoption may be lower than expected if the technology fails to address a consideration that influences adoption behavior. Second, resources may be wasted on features that influence stated intention, but which are overruled when it comes actually using a technology.

To better understand the intention-behavior gap in contact tracing, we conducted a survey of 290 U.S. residents in late December 2020, prior to widespread vaccine availability. The survey investigated factors related to both stated intention to install a contact tracing app, and whether or not respondents had actually done so. Because state-sponsored contact tracing technology had been deployed in some states but not others at the time of our survey, we were able to divide respondents into groups to understand what might cause an intention-behavior gap (Figure 1). The main purpose

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of our analysis was to investigate the extent to which an intention-behavior gap shaped app adoption. We investigated this question through the following research questions.

- **RQ1**: What are respondents' impressions toward contact tracing apps?
- **RQ2**: Do intentions toward installing a contact tracing app change based on whether one is available?
- **RQ3**: Among people for whom an app is available, what are the differences between (a) respondents who have actually installed the app and (b) respondents who say they would install but have not done so?

Through this survey, we identify that people's impressions of contact tracing apps were generally positive, although some participants expressed concerns about the potential for information leaks and relying on others to register to the app if they were infected. We find that people's intentions to install a contact tracing app were not significantly influenced by whether an app is widely available in their state. And finally, we identified that stated intentions to install and actually having installed an app appear to be shaped by different sets of factors. Most evidently, social norms were strongly associated with adoption behavior, and appeared to overrule concerns about privacy, which had a negative relationships toward stated intentions to install. Based on our analysis, we identify ways for designers to leverage the social nature of collective action by emphasizing positive social norms in technology designs.

Our findings build on past HCI research examining intention-behavior gaps impacted by technology use. Although past HCI research has contributed technologies which aim to overcome the intention-behavior gap [18, 33, 55, 73, 88, 96], there is a lack of research attempting to unpack the nature of these gaps around adoption of technology, particularly for public health. By unpacking factors that shape both intention and behavior related to installing a contact tracing app, we identify strategies for expanding their adoption.

2021 has seen the proliferation of vaccines in some countries, yet limited vaccine availability in many regions, poor uptake in others, and the spread of more infectious variants of COVID-19 mean that other control measures remain significant. Furthermore, as well as identifying strategies for improving the adoption of contact tracing apps, our findings contribute to knowledge about designing and deploying technologies for future challenges in which people are asked to take individual action to contribute to collective welfare.

2 BACKGROUND

2.1 Digital contact tracing apps

Contact tracing has conventionally been a manual process, where public health officials interview infected people and then warning people with whom they were in contact and asking them to self-isolate [40]. Mobile applications have been identified as a way to track and contain the spread of COVID-19, since the rapidity of the virus' spread and the fact that it can be spread presymptomatically or asymptomatically make it difficult to contain through manual contact tracing [29]. Although vaccines have become the foremost defense against COVID-19 infection, there is still a need for non-pharmaceutical interventions, such as contact tracing, social distancing, and mask wearing. Even though some regions have scaled back contact tracing efforts in recent months [78], researchers have found that vaccination alone is not sufficient to contain emerging viral variants such as Delta [80] and Omicron [89]. In reports published in May and June 2021, the World Health Organization has continued to emphasize contact tracing as an important strategy for containing COVID-19 [65, 66]. Furthermore, there continues to be development of new contact tracing applications both within the United States [58] and in other countries [61, 68].

A variety of implementations of digital contact tracing have been developed for COVID-19. The major differences are generally the method of detecting contact (e.g., GPS location tracking, Bluetooth proximity tracking, and QR codes), how data is stored (on a centralized server or decentralized across devices), and whether or not identifying information is collected [2, 50, 56]. 88% of U.S. apps and 37% of non-U.S. apps listed on MIT Technology Review's COVID Tracing Tracker use the Google-Apple Exposures Notification system [64]. This system uses Bluetooth to detect when two devices are in close contact (usually defined as 15 minutes or longer within 6 feet) and does not necessitate the collection of identifying data.

Regardless of implementation, contact tracing apps work best when used by a large portion of the population. Most regions have targeted an adoption rate of 60% of the population, although lower levels of adoption can still be effective alongside other measures [1, 41, 63]. In most regions of the world, people have a choice about whether to install and use a contact tracing app, and adoption has generally been lower than expected. A survey of United States residents in December 2020 found that 14% of the population were currently using a contact tracing app [22]. Only 24 states had released or were planning to release a contact tracing app [91] as of March 2021, but nonetheless this installation rate is lower than both early predictions and the 60% goal. The highest contact tracing app adoption rates in Europe are in Finland (45%), and Ireland (49%), though the mean installation rate across European countries is about 20% [8]. Even though adoption has been lower than hoped, researchers in the UK conducted both a modelling and a statistical analysis, which estimated that every percentage point increase in app update could reduce the number of COVID-19 cases by 0.8% (modelling) or 2.3% (statistical analysis) [98]. Accordingly, there is a great value to understanding what factors motivate decisions to install a contact tracing app.

2.2 From Intention to Adoption of Technology

Technology adoption research has produced many models for understanding factors that shape intentions and behaviors related to adopting and using technologies. The Unified Theory of Acceptance and Use of Technology (UTAUT) [93] is among the most influential of these models.

UTAUT builds upon the Theory of Planned Behavior [3], a psychological theory that views intention as the strongest predictor of people's behaviors. UTAUT includes three constructs that predict behavioral intention to use a technology: Performance expectancy, effort expectancy, and social influence. Although UTAUT has been used in a variety of studies, including about health informatics [e.g. 42, 44, 48, 59] and about adoption of contact tracing apps specifically [27, 87, 95], the variables in UTAUT are often defined using a single dimension, such as the social influence is typically operationalized as *people important to me think I should use the technology* [34]. This approach may not account for the complex and dynamics nature of cultural, organizational, and emotional factors, which are important to shape users' intention of adopting a technology. Thus researchers often add additional variables to account for these factors [7]. Specifically to the health and public context, recent studies have recommended leveraging existing social norms to encourage healthy pandemic behaviors [14, 38] as well as to encourage collective action [14, 83, 86, 99], including using messaging based on both descriptive norms such as beliefs about what most people do, and injunctive norms such as beliefs about what one *should* do [21].

Some recent studies have used UTAUT to predict adoption of contact tracing apps [27, 87, 95], offering some understanding of why people choose not to install the apps. In part, people are motivated by individual attributes such as attitudes about the perceived performance of the app [90, 92, 95], perceived ease-of-use [27], and personal innovativeness [95]. Adoption intentions are also shaped by social influence from others [74, 95], and situational variables such as the rate of infection at the time of the survey [36]. These studies occasionally presented conflicting perspectives on the impact of different factors on adoption. For example, although many studies identified privacy concerns as a deterrent to adoption [6, 36, 39, 51, 52, 74, 90, 95], others found that concerns about privacy were overruled by other factors [31, 92]. These conflicting findings may be due to differences in context and population among these studies.

Importantly, many studies about contact tracing app adoption have relied mainly on measures of individuals' intention to install an app, however, researchers have identified that people's actual adoption behaviors may not align with their intentions [90], suggesting the need to study the intention-behavior gap of installing the app. In terms of intention-behavior gap, Ajzen notes that intention and behavior measures vary in correlation, with regression coefficients generally between 0.3 to 0.6 [4]. In other words, technology adoption is subject to an intention-behavior gap, where intentions to use or to avoid using a technology are not always followed by actually doing so. Sheeran [77] summarized several explanations for the intention-behavior gap in social psychology research, such as people's intentions changing over time, different behavioral responses to intentions based on one's own attitude compared to those based on social norms, and personality and cognitive variables. Ajzen further emphasized that people do not always have control over their behavior, so "a low intention–behavior relation is a warning sign indicating that we may be reaching the limits of reasoned action" [4, p. 1115].

Although the nature of the intention-behavior gap has been a subject of significant inquiry in social psychology, this gap has received little attention in the HCI health community. Researchers have contributed novel technologies and interaction capabilities to address the gap and evaluated those strategies through relatively small-scale deployments and studies [e.g., 18, 33, 55, 73, 88, 96]. Less HCI work has examined how broad populations overcome or consider the intention-behavior gap when considering whether to adopt technologies for health, such as contact tracing apps.Likely due to its focus on supporting people to follow through on their intentions, HCI has generally focused on domains in which the *right thing to do* is commonly agreed upon, such as physical exercise [55] and avoiding food waste [33]. By contrast, opinions about the right thing to do are deeply divided in the context of the pandemic, and many who decide not to install a contact tracing app, or wear a mask, or get a vaccine have a strong intention *not* to take those actions. Thus, in the present paper, we interpret intentions on respondents' own terms – that is, both intentions to use and *not* use a contact tracing app are equally valid as analytic objects. Unpacking the reasons for the intention-behavior gap could provide a basis for designers and researchers to build more effective interventions for contact tracing, and contribute to our understanding of reasons for intention-behavior gaps in health technology more broadly.

3 METHOD

We conducted an online survey of 290 U.S. residents in late December 2020, before wide vaccine distribution had begun in the United States. At this time, contact tracing was viewed as one of the primary ways of controlling the spread of COVID-19. The overall purpose of the survey was to identify factors associated with contact tracing app adoption and use. At the time of our analysis, it was clear that a smaller number of people had installed contact tracing apps than had expressed their intention to do so, and this guided our attention toward an apparent intention-behavior gap. Given the timing of the study – shortly before vaccines distribution dramatically changed the overall strategy for containing the pandemic, and at a moment when contact tracing apps were available in almost half of U.S. States – a sizable portion of our respondents had had a chance to have installed a contact tracing app, and thus our survey responses were well-suited for investigating this gap. Furthermore, the United States is a context in which contact tracing apps are optional, rather than mandatory. Thus, this case provides suitable data for understanding individuals' intention and behavior toward apps that require collective use, but lack institutional structures to mandate adoption.

The 290 participants were recruited using Prolific.co, an online research platform. The study was configured using Prolific's represensitive sample feature, in which the sample is stratified by age, sex and ethnicity. Prolific takes a number of measures to prevent bots and retakes, such as requiring participants to have a unique, non-VOIP phone number, a unique PayPal or Circle account for payment, and limiting the number of accounts that can use connect using the same IP address [17]. The average approval rate for the participants was 99.3%, indicating that participants had almost never submitted data that was deemed unfit by previous researchers. . Participants lived in 43 unique states of the U.S. and were representative of the general population by sex, age, and ethnicity. Participant demographics are summarized in Table 1. 97.6% of participants indicated that they own a smartphone (N=283). This study was reviewed and approved by our institutional review boards.

3.1 Survey design

The survey included the following sections: Demographics, an introduction to contact tracing apps, questions about participants' attitudes towards contact tracing apps, trust in society, participants' working lives (for employed participants), and finally, questions about the pandemic in general. In general, the survey consisted of

Table 1: Demographic breakdown of our survey respondents.

Gender	Age	Race	Household income (USD)
Female: 142 (48.97%)	18-24: 47 (16.21%)	American Indian or Alaskan Native: 2 (0.69%)	< 10,000: 28 (9.79%)
Male: 142 (48.97%)	25-34: 74 (25.52%)	Asian: 24 (8.28%)	10,000 to -24,999: 37 (12.94%)
Non-binary: 6 (2.07%)	35-44: 58 (20%)	Black: 38 (13.1%)	25,000 to 49,999: 77 (26.92%)
	45-54: 47 (16.21%)	Latino: 13 (4.48%)	50,000 to 74,499: 59 (20.63%)
	55-64: 41 (14.14%)	Middle Eastern: 2 (0.69%)	75,000 to 99,999: 33 (11.54%)
	65-74: 21 (7.24%)	Multiracial: 18 (6.21%)	100,000 to 149,999: 34 (11.89%)
	75+: 2 (0.69%)	Prefer not to disclose: 2 (0.69%)	>150,000: 18, (6.29%)
		White: 191 (65.86%)	

Likert questions, and we additionally included some open-ended questions to allow respondents to explain their views in more detail. The complete survey is available in the supplementary materials.

Because there was not an app available in every state, and implementations differed slightly between states, we described a hypothetical contact tracing app in the survey. The app, called *COVID Contact App*, was a typified example of an app built using the Google-Apple Exposures Notification system. This description included a brief overview of the purpose of contact tracing apps, as well as description about how COVID Contact App worked. This description generally reflected designs of contact tracing apps built using the Google-Apple Exposures Notification system, such as relying on Bluetooth rather than location data, measuring close contact as spending 15 minutes or more within 6 feet of someone, and not collecting identifying information such as names or phone numbers.

We measured respondents' adoption intentions and behavior with the question, "What would your intention be towards installing COVID Contact App on your phone?" For people who had installed a contact tracing app, possible responses included, "I have already installed and am using a contact tracing app similar to this," "I have already installed a contact tracing app like this, but I am not using it anymore,". For people who had not installed a contact tracing app, responses consisted of a five-point Likert item from "I would definitely want to install it" to "I would definitely not want to install it."

To understand respondents' impressions toward the app itself, we expanded upon UTAUT. We asked how respondents' "performance expectancy", "effort expectancy", "social influence", "perceived privacy risks", and "the effect of the app on anxiety" shaped their motivations to install.

Performance expectancy is defined as "the degree to which an individual believes that using the system will help him or her to attain gains" in a given context [93, p. 447]. We map this to the context of the pandemic with three questions: First, the perceived ability of the app to help achieve the broader goal of preventing infection. Second, we asked about participants' potential doubt in the app's ability to function at all, since bugs are a potential risk. And third, we asked about skepticism regarding whether other people would register their infections, since this social component is required for apps to detect cases.

Past studies [87, 95] have operationalized effort expectancy based on the difficult of *using* contact tracing apps. To that end, we included a general measure about perceived ability to use the app and a question about participants' confidence that they know how to respond if they receives a notification. Additionally, we asked about perceived difficulty or inconvenience installing the app because users who are never infected and who never receive a notification may only ever interact with a contact tracing app during installation.

"Social influence" included if they knew app users or if anyone had recommended a contact tracing app to them, how they expected others to use these apps, and injunctive beliefs about whether they believed other people *should* install a contact tracing app.

A question about "perceived privacy risks" was included because privacy has been identified as a major area of concern in scholarship about contact tracing apps [6, 28, 69, 75]. To measure privacy risk, we asked about the extent to which participants were worried about information leaking to a third party.

Furthermore, questions about "the effect of the app on anxiety" were included because the pandemic has generally had significant effects on people's anxiety and mental health [20], and prior work has also suggested that contact tracing apps can impact peoples' mental health [47] and that anxiety shapes people's attitudes toward contact tracing [52]. Additionally, we asked an open-ended question, "How do you think daily life is affected by installing the COVID Contact App?"

When asking about the pandemic more generally, we included questions about various types of stress, derived from the COVID Stress Scales [84]. This further helped us investigate potential relationships between stress/anxiety and installing a contact tracing app.

3.2 Analysis

To understand the gap between intention to install and actual use, it was necessary to identify which respondents had access to a contact tracing app in their state. To do so, we referred to MIT Technology Review's COVID Tracing Tracker [72], which lists U.S. contact tracing apps by state. We additionally checked press releases and news articles to determine the release date of each app and removed one state which was released after our survey had been conducted. We also excluded two states that had only had a limited pilot release of an app at the time of our survey. 22 states had state-sponsored contact tracing apps at the time of the survey. Of those, 16 had been available for at least two months prior to the survey, 7 were released in November 2020, and California's CA COVID NOTIFY was released on December 11, 2020, one week prior to our survey.[1] Based on this variable, we categorized participants into two groups: respondents who live in a state where a contact tracing app was available at the time of the study (N=130) and those who live in a state where a contact tracing app was not available (N=160). The three states with contact tracing apps where we recruited the most participants were California (27 participants), New York (19), and Pennsylvania (15). Texas (23 participants), Florida (21), and Ohio (16) were the three states without contact tracing apps where we received the most responses.

Having identified states where contact tracing apps were available at the time of the survey, we divided respondents in order to address each research question. These groupings are presented in Figure 1.

To describe respondents' impressions toward contact tracing apps (RQ1), we assessed participants' self-evaluations of how effort expectancy, performance expectancy, privacy risk, and effects on anxiety would influence their decision to install. This helped identify what kind of concerns about the app participants felt were most important. We then qualitatively analyzed responses to the survey question, "How do you think daily life is affected by installing a contact tracing app?" We developed codes inductively, and two of the authors individually coded the responses. Across 10 initial codes, the first pass showed substantial agreement (Kappa: min = 0.77, min = 0.43, max = 0.97; Agreement: mean = 96%, min = 87%, max = 99.7%) . Disagreements were resolved through discussion among the authors. Based on this qualitative analysis, we summarized themes to explain respondents' impressions.

To address whether intentions toward installing a contact tracing app change based on its availability (RQ2), we examined differences between respondents based on whether an app was available at the time of the study. First, we examined the extent to which adoption intentions and behaviors vary among them. Additionally, we used Mann-Whitney U-tests to compare the following types of responses across these two groups:

- Attitudes about the contact tracing app
- Intentions to use app once installed (e.g. whether respondents intended to register their case to the app if infected, and how they intended to respond if the app notified them of exposure to COVID-19).
- Beliefs about how other people would use the app.

The results of these comparisons are presented in Section 4.2.

To unpack the differences between the groups in RQ3, we further divide this question into two sub-questions:

- **RQ3A**: Among people who live in a state where an app is available, what factors are associated with whether or not they actually installed an app?
- **RQ3B**: Among people who live in a state where an app is available and who have *not* installed it, what factors are associated with their stated intention to install?

[1]We had some concern that the short time between California's app being released and the time of our survey would skew our results. Twenty-seven of our respondents resided in California, of which 48% (n=13) had installed the app. This high adoption rate suggests that people were sufficiently aware of the app and had opportunities to install it, such that the short time since its release did not significantly bias our results.

By asking these two questions, we disentangle factors that are important for driving adoption behavior from those that may influence stated intentions but fall short of affecting behavior.

We used two multivariate regression models to address these questions - Model 1 identified factors associated with actual app installation behavior (RQ3A), and Model 2 focused on those who had not installed the app and identified factors associated with intention to install (RQ3B). The dependent variable in Model 1 measured adoption behavior using a dichotomous variable indicating whether respondents said they had installed a contact tracing app or not. The sample consisted of those respondents who live in a state where an app was available at the time of the survey. We used a logistic regression analysis, and because of the relatively small sample size, we applied the Firth procedure to mitigate parameter estimation bias [23, 30].

To examine stated intention that was not accompanied by behavior, the sample for Model 2 was respondents who live in a state where an app was available at the time of the study, and who had not installed the app. The dependent variable was stated intention to install a contact tracing app, on a five-point scale from "I definitely do not want to install it" to "I definitely want to install it." Because the dependent variable is an ordinal Likert scale, we used an ordered logistic regression analysis.

Independent variables for these analyses were selected based on Spearman correlations with variables about having installed or intending to install a contact tracing app, while following theoretical guidelines to include variables about performance expectancy, effort expectancy and social influence. Variables about effort expectancy were tested and then removed from our analysis because we found no statistically significant association with our dependent variables and they had negligible effect on the overall explained variance of either model. We considered additional variables for the regression analyses, including measures of effort expectancy and whether participants knew someone who had been infected. We removed these from our analysis because they did not have a statistically significant association with our dependent variables and had a negligible effect on the overall explained variance of either model. Variables measuring income, race, gender, and employment status were excluded for the same reason. We additionally considered including a variable measuring participants' level of trust in the government, and excluded it because its effect was explained by other variables. Because our analysis involved focusing on the subset of participants for whom an app was available (n=130) and then further, those who had not installed it (n=91), we sought to the number of variables to avoid overfitting given those sample sizes.

A table summarizing the independent variables from these analyses is included in the supplementary documents. Both models were subject to a link test for model specification, which found no specification errors and a test of Variance Inflation Factors (all < 2.3) indicated that collinearity did not occur in either model. For both models, explained variance is presented as McFadden's pseudo R^2. The explained variance for Model 1 (pseudo R^2 = 0.275) is lower than for Model 2 (pseudo R^2 = 0.492). In general, McFadden reports that pseudo R^2 scores are lower than R^2 in linear regressions, and that a score of 0.2-0.4 represents an "excellent fit" [54, p. 307]. The full regression model is presented as a supplementary document, and key results are presented in Section 4.3

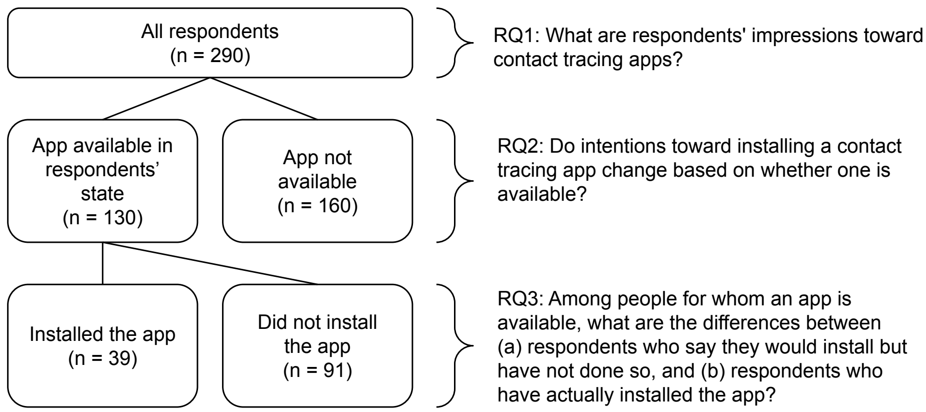

Figure 1: Respondents grouped for each research question

4 FINDINGS

In this section we present the results of our analysis. Section 4.1 addresses RQ1 by summarizing respondents' overall impressions of the contact tracing app described in the survey. Section 4.2 addresses RQ2, exploring whether intentions to install a contact tracing app were different depending on whether or not an app was available in respondents' states at the time of the survey. Section 4.3 addresses RQ3, identifying the common/different factors contributing to actually installing a contact tracing app and stated intention to do so.

4.1 Attitudes toward contact tracing apps

This section addresses RQ1, "What are respondents' attitudes toward contact tracing apps?" We summarize respondents' impressions of the typified app described to them in the survey. We discuss these impressions in relation to the extent to which they said beliefs about effort expectancy, performance expectancy, privacy risk, and effects on anxiety would effect their decision whether to install a contact tracing app, which are summarized in Figure 2.

When asked how they think daily life is or would be impacted by installing COVID Contact App, many respondents indicated in the free-text field that a contact tracing app would help them be more aware and/or safe during the pandemic. For example, P53 said, "*I think it could be beneficial because you can't just tell that someone has it or has come into contact with it so if I'm with someone long enough and the app goes off, it would be nice instead of me just unknowingly going around and potentially spreading it and killing people.*" Additionally, respondents were optimistic that using the app would reduce their anxiety about being infected with COVID-19, and this motivated their intention to install. 50% of participants said that the goal of reducing anxiety would have a significant or very strong influence on whether or not to install the app. For example, *"[It] might make me more relaxed about going to stores and stuff"* (P112). Conversely, only 10% of participants expressed concern that the potential for the app to increase one's anxiety about being infected would impact their decision.

However, participant responses suggested that most participants thought the app would have minimal impact in their lives. Sometimes this was framed as a positive quality, meaning the app would sit unnoticed in the background but become useful upon exposure — e.g., *"I don't think it would have a significant affect on my daily life unless I got a notification that I was around someone who tested positive.* (P13). In other cases, the app was described as having little effect at all: e.g., *"It would not affect me"* (P56); *"It wouldn't change anything"* (P136). For some participants, the perceived lack of effect was because the they were already isolated: e.g., *"For me, it wouldn't make any difference, since I am almost never in close contact with anyone else. That's why I don't need to install the app. I stay at home all the time"* (P67).

However, participants had some concerns about whether other people would honestly register their results to the app if they test positive for COVID-19. 32% of participants said the feeling that they could not trust people to register would have a significant or very strong influence on their installation decision, compared to 45% who said such a concern would have little to no influence. Some respondents challenged the effectiveness of an app that relied so much on other people: *"Would there even a point if so many people do not take COVID19 seriously? The app depends too much on the goodwill of people and currently that's not working"* (P154). Similarly, some positive evaluations of the app were accompanied by qualifiers like *"provided that the majority of people had it"* (P35).

Additionally, participants expressed some concern with contact tracing apps leaking information to third parties. 46% said this concern would have a significant or very strong influence on their decision whether to install the app, compared to 24% who said it would have little or no influence. Consistent with prior research, [6, 36, 39, 51, 95] several participants expressed concern about the app being used for surveillance, such as remarks that the app *"would make me feel very monitored and uneasy. Big Brother State"* (P130) and that *"I don't trust the presence of an app that tracks your every movement and sends that data elsewhere"* (P14). Another perceived harm was that the app could make respondents spend more time thinking about the pandemic, potentially adding to their anxiety, e.g., *"I think it would make me a nervous wreck. So many people*

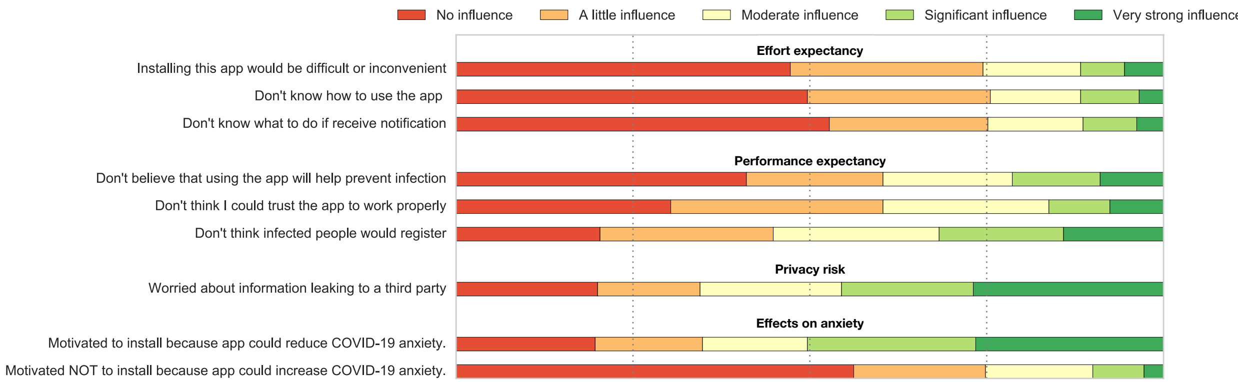

Figure 2: Participants generally were not deterred by beliefs that the model contact tracing app would require significant effort or might not work effectively for tracing, though expressed some concerns about information leaking to a third party.

have it here and every time I would get a phone signal, I would have anxiety" (P175). This type of concern was sometimes compounded by skepticism about the notifications' accuracy: "*[I] would find it somewhat stressful if I were at the grocery store and it went off every five minutes. Some of the folks who have registered may no longer have the virus, so I'm skeptical how useful it would be to know everyone you come in contact with that may have had it*" (P135).

In sum, the results show that respondents were overall positive about the app, although there were mixed opinions about data privacy and counting on others to use the app effectively. Additionally, respondents generally believed the app would have minimal effect on their everyday lives.

4.2 Effect of app availability on intention to install

This section addresses RQ2, "Do intentions toward installing a contact tracing app change based on whether one is available?"

Figure 3 compares intentions to install and actually installing, comparing between respondents in states where an app was not available and states where an app was available. The number of people who generally agreed that they would or did install a contact tracing app was roughly the same in both groups (55%). In states where a contact tracing app was not available, 52% indicated they probably or definitely would install an app, and 3% reported having installed one.[2] In states where an app was available, the portion of people who said they probably or would definitely install an app was lower (25%) but this was offset by the 30% who reported having installed one. Although we do not have a longitudinal measure of attitudes before and after apps became available in each state, participant's responses lead us to estimate that slightly over 50% of respondents who say they would probably or definitely install a contact tracing app would actually do so.

Mann-Whitney U-tests found little difference between these two groups. For almost all variables describing impressions about the contact tracing app, intentions to use it, or beliefs about how other people would use it, p was > 0.05. Exceptions were that people for whom a contact tracing app was available were more likely to agree that they would be motivated to install the app as a way to reduce their anxiety about being infected with COVID-19 (Mann Whitney U = 8546, $p < 0.01$). Additionally, respondents for whom an app was available were more likely to agree that, if *other people* were notified by the app of exposure to someone with COVID-19, those people would tell their family and friends (Mann Whitney U = 8810.5, $p < 0.05$) and get tested (Mann Whitney U = 8955, $p < 0.05$).

These results suggest that overall intentions to install a contact tracing app are not significantly different in regions where an app is available or not available. Accordingly, it is unlikely that the intention-behavior gap is explained by some change of opinion caused by apps becoming available. Consequently, our results do not

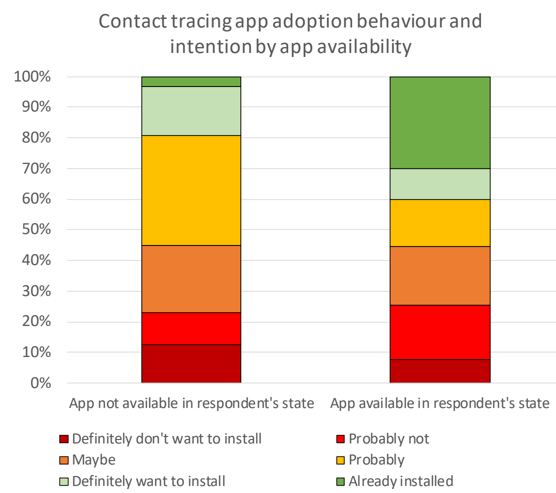

Figure 3: Installing or intending to install a contact tracing app over app availability in respondents' states.

[2] There are some reasonable explanations for why a small number of respondents could install an app even though they live in a state where none is available. For example, one respondent wrote a note explaining that they installed an app for their neighboring state since they live near the border.

show evidence that people consciously change their mind between imagining a hypothetical contact tracing app and when faced with the actual decision of installing an app that has been released to the public. Rather, the gap appears to be between individuals' intention and behavior.

4.3 Installing and intending to install

Figure 4 summarizes the result of a logistic regression analysis to address **RQ3A**: "Among people who live in a state where an app is available, what factors are associated with whether or not they actually installed an app?"

Three variables had statistically significant associations with having installed a contact tracing app. First, respondents who knew at least one person who used a contact tracing app were more likely to have installed an app themselves (OR = 7.712, 95% confidence interval = 2.49, 23.92). Additionally, respondents who expressed a believe that everyone should use the app were also more likely to have installed it themselves (OR = 3.004, 95% confidence interval = 1.49, 6.04). Finally, respondents were less likely to have installed the app if they expressed a stronger belief that other people would self-isolate if they were sent an exposure notification by the app (OR = 0.347, 95% confidence interval = 0.18, 0.68). Additionally, we included age as a control variable, and older respondents were slightly more likely to have installed the app (OR = 1.045, 95% confidence interval = 1.00, 1.09).

As described in Section 4.2, 25% of respondents who lived in a state with a contact tracing app reported that they intend to install it, but had not actually done so. We investigated this group through **RQ3B**: "Among people who live in a state where a contact tracing app is available but who have not installed it, what factors are associated with their stated intention to install?" Figure 5 shows that stated intentions to install a contact tracing app were higher among respondents who knew at least one person who used a contact tracing app (OR = 5.434, 95% confidence interval = 1.55, 18.99), who expressed higher levels of worry about themselves or their family catching the virus (OR = 1.621, 95% confidence interval = 1.03, 2.54), or who expressed a believe that "everyone" should use the app (OR = 1.979, 95% confidence interval = 1.23, 3.18). Conversely, stated intentions to install a contact tracing app were lower among respondents who expressed that worry about information leaking to a third party was a significant factor for their decision (OR = 0.587, 95% confidence interval = 0.40, 0.86).

In combination, these analyses show us that *knowing at least one person who uses a contact tracing app* and *believing that everyone should install a contact tracing app* were strongly associated with both actual adoption and stated intention. Surprisingly, *belief that others would self-isolate in response to an exposure notification* was negatively associated with having installed an app, but was not associated with stated intention. Finally, *stress about being infected* and *worries about information leaking to a third party* were only associated with stated intention, and not with actual behavior. In sum, social influences were the strongest motivators of both intention and behavior, and thus may be the most significant factors for encouraging greater adoption.

5 DISCUSSION

Respondents' overall impressions of the presented contact tracing app were positive. Importantly, positive impressions were moderated by a common belief that the app would have little to no effect on daily life. Generally, participants viewed the lack of major everyday impact as a positive, finding it unobtrusive. By contrast, some respondents were concerned that the app could be too intrusive, sending too many notifications or otherwise causing anxiety.

To investigate the intention-behavior gap, we identified two factors that were associated with stated intention to install the app, but not with actually installing a contact tracing app. These two factors are stress and privacy concerns. First, stress about oneself or one's family being infected, which was positively associated with intention to install. Research suggests that fear is an effective driver of behavior change only if perceived self-efficacy is high [97]. However, it is plausible that stress about infection is highest among people who do not feel that they have self-efficacy in relation to the spread of COVID-19. Second, although concerns about information leakage were negatively associated with intentions to install, they too had no effect on behavior in our multivariate analysis. This suggests privacy concerns were overruled by other factors.

Different from the intention to install, the dominant factors associated with actual installation of a contact tracing app were all related to social influences. Because these appear to be such an important factor, we unpack these further in Section 5.1. Even though privacy concerns were ultimately not associated with installation behavior, many respondents had at least some concern about information leakage to third parties. This merits further consideration, which we present in Section 5.2. Finally, based on our analysis, we present recommendations for designers and organizations promoting the use of contact tracing apps in Section 5.3.

5.1 Social influence and social norms

We found that both an injunctive norm (believing that everyone should install the app) and a descriptive norm (knowing other people who use a contact tracing app) had a positive influence on both adoption intention and behavior. This is consistent with findings in past studies that contact tracing app adoption is shaped by social influence [27, 74, 95]. However, where prior research has operationalized social influence as a single factor ("people important to me think I should use the technology") our findings identified multiple types of social influence.

Social psychology research has identified descriptive norms as significant drivers of collective action behavior [99], so the effect of knowing at least one other person who uses a contact tracing app on adoption is not surprising. However, descriptive norms can have negative effects when they show a desirable behavior to be rare, because people change their behavior towards whatever is more common [83]. In such cases, messaging about injunctive norms can overcome this "boomerang effect" [99]. This can explain why believing that everyone should install a contact tracing app was statistically significant in our models–this injunctive norm can motivate installation even among people who do not know anyone who uses a contact tracing app.

Another dimension of the influence of descriptive norms is that contact tracing apps are subject to network effects. Their utility

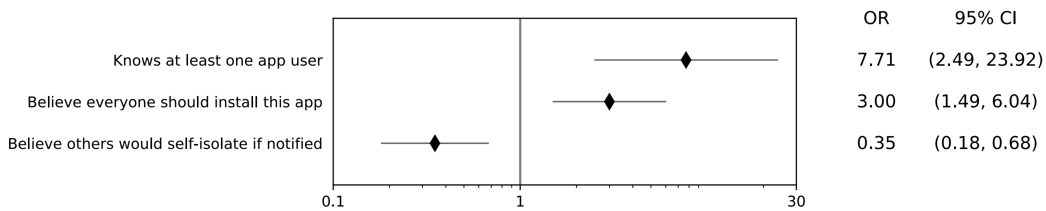

Figure 4: RQ3A: Factors associated with having installed a contact tracing app, among participants for whom app is available. Results are reported as odds ratios. An odds ratio less than 1 indicates there is a negative effect, and greater than 1 indicates a positive effect.

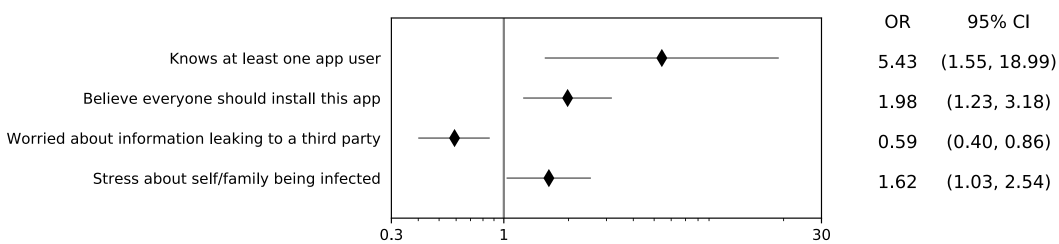

Figure 5: RQ3B: Factors associated with stated intention to install a contact tracing app, among participants for whom app is available and who have not installed it. Results are reported as odds ratios. An odds ratio less than 1 indicates there is a negative effect, and greater than 1 indicates a positive effect.

increases if they are used by many people, and, for each individual, their utility is proportional to the number of other app users with whom that individual comes into contact with. More generally, this aligns with work showing that one of the mechanisms through which social norms influence collective action is by affirming the efficacy of both one's own contribution and that of others [16]. Given the sharp skepticism that some respondents expressed towards relying on others to take COVID-19 seriously, if respondents observe that no one around them is using a contact tracing app, they may conclude that the app will not be effective even if they evaluate it highly in other regards.

It is noteworthy that the other significant descriptive social norm, believing that others would self-isolate if sent an exposure notification by a contact tracing app, was negatively associated with actual behavior, and did not have a significant association with stated intentions. This suggests that beliefs about other people's behavior could offer a partial explanation for the intention-behavior gap. We present some possible explanations. First, respondents who strongly believe that others would self-isolate may feel it is unnecessary to use a contact tracing app themselves. This could be interpreted as the bystander effect [24], where one is less likely to take action themselves if perceived responsibility is diffused among other people. This interpretation also implies that those who feel they could not rely on others may feel obligated to take more measures to protect themselves. Another possibility is that respondents who believe other people would self-isolate in response to an exposure notification feel that installing the app would obligate them to do so. Given that some respondents expressed apprehension about "*constantly getting notifications*" (P25), some might be concerned that they would be expected to follow a norm of self-isolating every time they got a notification. Self-isolation, in particular, is a high-cost endeavor for almost everyone. Working people may lose income if they are required to self-isolate, and even non-working people or those who work from home may be deeply inconvenienced and lose opportunities to socialize or meet with family. This interpretation is aligned with the low cost hypothesis, which asserts that attitudes only predict behavior if the costs of that behavior are low [25]. In sum, descriptive norms may be a deterrent to using technologies if they suggest costs of that use, or if the collective purpose of that technology is regarded as already fulfilled by others.

These interpretations raise the question about why such a backfiring effect is not evident in response to knowing other people who use a contact tracing app, which was plainly a positive influence on adoption. One consideration is that when respondents know whether a person around them has installed a contact tracing app, that person is likely at least a somewhat strong tie [35]. Past research has suggested that tie strength is an antecedent of social influence with regard to technology adoption [10, 85]. The behaviors of close ties such as friends, family, and close community members are likely to carry normative weight because of desires to conform to norms associated with one's social group [34]. This kind of influence could also play a role in addressing privacy concerns or other doubts about the app, since people are likely to defer to trusted peers' judgment to some extent. By contrast, beliefs about what "most other people" would do may lack influence because "most other people" are outside of one's own group, especially given the divisiveness of rhetoric and behavior around the pandemic in the United States [49].

5.2 Privacy concerns

Concerns about privacy leaks to third parties were relatively common and were influential toward people's stated intentions to install an app. However, this influence seemed to be overruled by other considerations when it came to actually installing. This finding offers some explanation for mixed results between prior studies, some of which have identified privacy concerns as a significant factor toward adoption [6, 36, 39, 51, 52, 74, 90, 95], while others have found privacy concerns to be insignificant compared to other factors [31, 92].

In cases where respondents who were concerned about information leakage caused by a contact tracing app, there appears to be a privacy paradox, the phenomenon that people are concerned about how digital technologies impact their privacy but take minimal action to protect their personal data [11]. Social factors have been used to explain the privacy paradox in contexts of online social networking [82] and online location disclosure [100], where perceived social benefits are among the factors that shape disclosure. Given the strong effect of social norms in our models, it is likely that social factors explain the apparent paradox in this context as well. The strength of the association between knowing other people who use a contact tracing app and installing, it is possible that adoption behavior was shaped by herding, when "a person follows others when adopting a technology, even when his/her private information suggests doing something else" [81, p. 1016]. Moreover, people often have knowledge gaps about how their information is used in digital systems, and thus it is difficult for them to make informed assessments [12]. Another possibility is that people are willing to self-sacrifice to help others, and so they set their privacy concerns aside to contribute to the public health benefits of contract tracing [76]. It seems reasonable that people with this attitude would be more likely to believe that everyone should install a contact tracing app, so belief in this injunctive norm offers some further explanation.

In both cases, some contact tracing app users could have unresolved concerns about information leakage. Thus, although our results are consistent with some prior work that has concluded that concerns about losing privacy are not significant factors for adoption [92], there are possibilities that latent privacy concerns could affect long-term trust. Perceived costs of sharing data, including concerns about privacy, have been identified as a motivation for abandoning technology [9, 26]. The number of people who have uninstalled a contact tracing app after having installed one seems to be small [15], so abandonment may not be an immediate concern for adoption rates. However, distrust can persist long-term and so could lead to hesitancy toward future interventions [43]. Long-term trust could be nurtured through designs that genuinely respect users' privacy, are transparent about what data is collected and how it is used, and function well so the individuals' sacrifices are felt to be worthwhile.

The corollary implication of this finding is that being unconcerned about information leaks was not a sufficient motivation to install a contact tracing app. Addressing privacy concerns may be a vital first step in the intention-to-behavior pathway, as it could increase intentions to install. However, this is not strong enough to motivate actually installation behavior. As a consequence, although it is important to address privacy concerns, this must be accompanied by nurturing other motivations to install, such as presenting compelling evidence that the technology can be effective at protecting oneself and members of one's community.

5.3 Design implications

Given the association between social norms and app adoption, focusing health communication on social responsibility has been identified as a way to increase public acceptance [87]. While public health agencies can leverage such messaging on a broad scale, our analysis emphasizes the value of word-of-mouth for encouraging adoption, similar to Sharma et al. [76]. In suggesting this direction, we first consider that some contact tracing apps, once installed, are so invisible that users have had confusion about whether they were working at all [71, 101] With designs of that sort, there may be little reason or opportunity for people to let others know they are using a contact tracing app. However, doing so could directly increase the number of people who know someone who uses the app, which is likely to increase adoption. Some contact tracing apps include buttons to share the app with others (e.g., on social media or by messaging), which is a simple and valuable design decision to increase social visibility. However, since these apps usually operate invisibly in the background, after the initial setup, people may not open the app and see the sharing features in the first place.

To nurture engagement of the app, contact tracing apps may communicate up-to-date safety information or pandemic-related news. However, in the context of COVID-19 contact tracing, there are some significant challenges that must be considered regarding this sort of recommendation. One of the benefits of digital contact tracing is that it is less burdensome than human contact tracing [52]. In our study, too, respondents who described the app as having little effect on their lives unless it detects an exposure viewed this as a good thing. Thus, any features that create a perceived burden are likely to be viewed negatively. This is especially a concern because there is evidence that frequently accessing news and information about the pandemic is associated with high levels of anxiety [32, 60]. One solution here is to avoid push notifications, stress-inducing news, or other features that could induce a sense of burden. Further, intense polarization in the U.S. (and other countries) could make it difficult for a contact tracing app to deliver pandemic news or information that would be regarded as appropriate by everyone. These caveats limit the potential of these suggestions for contact tracing, however we believe they could be useful for related contexts in which individuals' technology use serves a collective good, such as projects targeting environmental change.

We present two additional recommendations for increasing social visibility while avoiding placing a burden onto users. The first is to better utilize the app's existing features. Specifically, contact tracing apps may send regular status updates, such as iPhones running Apple's Exposures Notification system, which send a periodic message stating, "Your iPhone continues to look for possible exposures on your behalf." These messages could be revised to reinforce an injunctive norm that having the app installed is a good thing, e.g., "You're keeping your friends, family, and community safe" or to encourage users to share the app with people they know. Past research has recommended positive reinforcement as a way of prolonging positive emotions that are felt immediately after activities like running, leading to higher engagement in those behaviors [55]. In the context of contact tracing, adding positive reinforcement to the existing notifications provides an opportunity to boost positive emotions associated with the app and to encourage sharing with others. Second, health agencies and app developers could encourage sharing outside of the app itself. For example, by providing frames or badges for social media profile pictures, which could say something like, "I installed [name of contact tracing app]." This recommendation applies to domains beyond contact tracing. For example, Facebook has a feature allowing people to display "I got my COVID-19 Vaccine" frames around their profile [37]. These are potential ways to encouraging social sharing without creating a perceived burden associated with the app itself.

Finally, given that some people install a contact tracing app despite privacy concerns, it is important to reassure them that their trust was not misplaced. To that end, contact tracing apps should follow ethical guidelines for privacy such as allowing users to delete their data, avoiding permanent storage, and not using data for purposes beyond contact tracing [57]. Additionally, in agreement with past work that has advocated transparency about how data is used [76, 90], we suggest that contact tracing apps could provide a summary of what data has been collected, what it means, and what measures were taken to protect that data. This would provide an option for greater engagement, allow users to understand how the app works in more detail, and address latent privacy concerns which may be present among some users. Past research has suggested that informed assessments can override initial intuitive assessments of privacy risks [67], and this is supported by an analysis that found that privacy concerns among users of Germany's *Corona-Warn-App* decreased after they actually used the app [62]. Further, informing users about privacy implications of usage decisions at the time they are made has been shown to be effective [45]. Presenting users with a clear account of how their data is managed would allow them to make informed decisions, not based on a privacy policy or app permissions, but rather by understanding how the app works with their data on an ongoing basis. We acknowledge, however, that addressing privacy concerns within an app-design itself is a partial solution. People with intense distrust towards apps are unlikely to be swayed by assurances provided within the apps themselves. Further, Contact tracing apps are part of a complex socio-technical health infrastructures, and thus it is important that they be supported by clear messaging and effective policies by governments and public health agencies.

Across our recommendations, it is important to consider how beliefs about which other people are close or trusted ties vary across cultures. In Japan, for example, prior work has shown that due to intense stigmatization about infection with COVID-19, some people do not want the people around them to know they use a contact tracing app [46]. In other words, the "others" to which people are willing to disclose their activities are not universal. Accordingly, there is a potential that making the pro-social technologies visible could have negative impact on adoption in some contexts. To that end, it is important not to take a one-size-fits-all solution, but rather to carefully consider how social influence operates in specific contexts.

Throughout our recommendations, we have identified caveats and considerations specifically related to the COVID-19 pandemic. Many of our recommendations to leverage social norms to encourage technology adoption may also extend to other forms of individual action that serve collective goods. However, to avoid imposing unwelcome social visibility, any features that enhance a technology's social visibility should be optional, and cues supporting them should be encouraging but not forceful.

Finally, we acknowledge that aiming to address the intention-behavior gap in contact tracing through improving design presumes that the technology is beneficial for individuals. The HCI literature has pointed to important concerns around contact tracing's privacy, accuracy, and access [5, 79], which our findings and others' work show align with what people weigh when evaluating the technology [39, 46, 52, 90, 95]. Like in other technology domains [13, 26], it is worthwhile to consider normalizing non-use and abandonment as part of people's experience using contact tracing technology. Such thinking likely requires adjusting expectations around the widespread adopting of the technology. But doing so can move our thinking from contact tracing technology as tech solutionism [70] towards better understanding and accounting for its potential negative effects and shortcomings, and improving its utility in light of them.

6 LIMITATIONS

Our measure of app availability only indicates that a contact tracing app was available in the respondents' state at the time of the survey. It does not tell us if the respondent is aware that the app is available. Similarly, our models do not have any metrics about the level of marketing of the app, how long it has been available, or any other clues about how likely participants are to be aware of the app's availability. As described in Section 3.2, release dates of the apps varied relative to when we conducted the survey, which could have affected installation rates.

Past work has identified an interaction between education level and the degree to which perceived usefulness is associated with intent to use a contact tracing app [92]. Since education level was not included in our survey, we were unable to consider this dimension.

Our analysis involved narrowing the sample for RQ3, such that this part of the analysis focused only on respondents living in a state where a contact tracing app was available. We compared the results presented in Figure 5 with a version of the analysis that included all respondents and the results were very similar. Thus, we believe our results can be generalized across our respondents, and the decision to limit the scope of our analysis in RQ3 allowed us to address that question more precisely than if we had included all respondents. Nonetheless, it is possible that relationships with small effect sizes could have required larger sample sizes to be statistically significant in our analyses to address RQ3A and RQ3B. Specifically, future work may benefit from larger sample sizes to unpack potential interactions or subtle correlations with household income, cultural background, education, political views, and pandemic-related information practices. Similarly,as explained in

Section 3.2, we removed a measure of participants' trust in the government from our analysis because its effect was explained by other variables. However, given the strength and diversity of opinions about government responses to COVID-19 in the United States, a more nuanced measure of trust in different levels of government could have offered more explanatory power.

While our analysis focuses on contact tracing apps, these must be employed as part of a larger healthcare strategy. There are significant limitations to the accessibility of smartphone-based health technologies, even amongst those who intend or desire to use them. For example, only 85% of U.S. adults own a smartphone, and this drops to 61% for people over 65 years of age[19]. When allocating resources for healthcare support, governments and public health agencies should implement systems that fit with their constituents' reach, goals, and existing practices.

7 CONCLUSION

Through a survey of 290 U.S. residents, we investigated motivations for intending to and actually installing a contact tracing app. We found evidence to support the existence of an intention-behavior gap, and that social influences were the largest motivators of actual behavior. Although factors such as privacy concerns had an affect on stated intentions to install, it seems that social influences overruled those concerns with regard to actually installing a contact tracing app. We suggest that design strategies to increase the social visibility of contact tracing app usage could communicate descriptive social norms. We also identify opportunities to reinforce injunctive norms without increasing the perceived burden of using these apps. By unpacking the intention-behavior gap in the context of contact tracing apps, we identified opportunities to leverage social norms in technologies that ask individuals to take action to contribute to collective social goods.

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