Post-Pandemic Data Privacy: Contextual Acceptance of COVID-19 Mitigation Mobile Applications in the US

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Abstract

Background: The COVID-19 pandemic gave rise to countless user-facing mobile applications to help fight the pandemic ("COVID mitigation apps"). These apps have been at the center of data privacy discussions because they collect, use, and even retain sensitive personal data from their users (e.g., medical records, location data). The U.S. government ended its COVID-19 emergency declaration in May 2023, marking a unique time to comprehensively investigate how data privacy impacted people's acceptance of various COVID mitigation apps deployed throughout the pandemic.

Objective: This research aims to provide insights into health data privacy regarding COVID mitigation apps, and policy recommendations for future deployment of public health mobile apps through the lens of data privacy. This research explores people's contextual acceptance of different types of COVID mitigation apps by applying the privacy framework of Contextual Integrity. Specifically, this research seeks to identify the factors that impact people's acceptance of data sharing and data retention practices in various social contexts.

Methods: An online survey was conducted by recruiting a simple US representative sample (N=674) on Prolific in February 2023. The survey includes a total of 60 vignette scenarios representing realistic social contexts that COVID mitigation apps could be used. Each survey respondent answered questions about their acceptance of 10 randomly selected scenarios. Three Contextual Integrity parameters (attribute, recipient, and transmission principle) and respondents' basic demographics are controlled as independent variables. Regression analysis was performed to determine the factors that may impact people's acceptance of initial data sharing and retention practices via these apps. Qualitative data from the survey was analyzed to support the statistical results.

Results: Many CI parameter values, pairwise combinations of CI parameter values, and some demographic features of respondents significantly impact their acceptance of using COVID mitigation apps in various social contexts. Respondents' acceptance of data retention practices diverged from their initial sharing practices in some scenarios.

Conclusions: This study showed that people's acceptance of using various COVID mitigation apps depends on specific social contexts including type of data (attribute), recipients of the data(recipient), and the purpose of data use (transmission principle). Such acceptance may differ between the initial data sharing and the retention practices even in the same scenario. Study findings generated rich implications for future public health mobile apps regarding data privacy, long-term strategies, and deployment considerations.

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Conclusions: This study showed that people's acceptance of using various COVID mitigation apps depends on specific social contexts, including the type of data (*attribute*), the recipients of the data(*recipient*), and the purpose of data use (*transmission principle*). Such acceptance may differ between the initial data sharing and data retention practices, even in the same context. Study findings generated rich implications for future pandemic mitigation apps and the broader public health mobile apps regarding data privacy and deployment considerations.

Keywords: data privacy; health privacy; COVID-19; mobile applications; contextual integrity

Introduction

Background

To combat the COVID-19 pandemic, countless user-facing mobile applications ("COVID mitigation apps") have been developed and deployed around the world [1-2]. These apps provide various functionality, including contact tracing [3], symptom self-checking [4], test result reporting (e.g., CoVerified [5]), and proof of vaccination (e.g., Israel Green Pass [6], Excelsior [7]). However, low adoption rates often undermine the real-world impact of these apps [8], partially caused by people's data privacy concerns around how these apps handle various sensitive personal data, including medical records and phone-based location data [9-10].

Public health priorities have changed throughout the COVID-19 pandemic [11], resulting in evolving needs for pandemic mitigation apps. Some apps deployed early in the pandemic with narrow functionality (e.g., symptom self-checking) became obsolete, while other apps are likely to remain useful post-pandemic (e.g., test result reporting). The US ended the COVID Public Health Emergency on May 11, 2023 [12]. It is time to comprehensively examine user privacy across different types of COVID mitigation apps developed in this pandemic. Specifically, we aim to investigate three types of COVID mitigation apps with broad utility in future public health crises, namely, contact tracing, test result reporting, and proof of vaccination.

We conducted a vignette survey study that applied the privacy framework of Contextual Integrity (CI) [13] to examine people's acceptance of how COVID mitigation apps could handle their personal health data in various social contexts. This research informs the design and deployment of future public health apps and relevant mandates around these apps from a privacy-centric perspective. Insights from this research could encourage the adoption of future public health apps by addressing people’s data privacy concerns in diverse social contexts.

Prior work: Data Privacy and the Adoption of COVID Mitigation Apps

Research examined the adoption of mobile technologies for pandemic mitigation worldwide, which primarily focused on contact tracing apps [3,14-17]. Generally, adoption rates are high for COVID mitigation apps backed by government mandates (e.g., Aarogya Setu [18] in India, HaMagen [19] in Israel), but low for apps relying on users' voluntary installation (e.g., COVID exposure alerts in the US). A multi-country study shows that people in collective cultures are more likely to adopt contact tracing apps than those in strong individualistic cultures [20].

Among all the factors impacting user adoption of COVID mitigation apps [16-17, 21-23], data privacy stood out as a major concern [3, 9-10, 20, 24-25]. Recent qualitative and mixed-methods studies also unpacked individual users' complex decision-making process, including data privacy considerations when adopting COVID mitigation apps [26-27].

However, most studies heavily focused on initial adoption but overlooked the continued use or future use of these apps post-pandemic. Also, many studies only examined a single app type [3, 9-10, 26-27], neglecting the fact that multiple types of apps can be used together to fight the pandemic. **Our study bridges these gaps by examining three major types of COVID mitigation apps with long-term utility in future public health crises.**

Another gap in the literature was the retention and re-use of personal data collected by COVID mitigation apps. Data retention is central to privacy law discussion [28-29] and affects users’ willingness to share personal information [30]. Currently, there is no clear guidance on how various data collected by these apps should be retained, while controversial re-use of such data by law enforcement have been reported [31-32]. Misuse of retained data from COVID mitigation apps can have dire privacy consequences. **Our study provides a new understanding of users’ attitudes towards COVID mitigation apps’ data retention.**

Theory: The Privacy Framework of Contextual Integrity (CI)

People’s data privacy attitudes towards computing technologies differ in various contexts [33-35], including who collects the data, the purpose of the data collection, and the specific ways the collected data will be used, processed, or shared. Haargittai et al. [23] found that US participants’ willingness to adopt contact tracing apps differs by the providers of the apps; Zhang et al. [36] revealed that people's acceptance of vaccination certificates varies in diverse real-world scenarios. However, traditional privacy theories (e.g., public/private dichotomy) fail to consider the contexts for computing technologies’ complex data practices [37-38].

Privacy as Contextual Integrity (CI), conceptualized by Helen Nissenbaum [13], is a rising privacy framework to examine computing technologies’ highly complex data practices. CI defines privacy as

the appropriate flow of information that follows established **information norms** in a particular society or culture. According to CI, **information norms can be captured in five CI parameters**: ***sender*** (who sends the data), ***recipient*** (who receives the data), ***subject*** (whose data), ***attribute*** (type of information), and ***transmission principle*** (TP thereafter, conditions of the flow). Empirically, we can observe **information norms** from people's privacy attitudes towards different information flows exhibited in various data practices.

Compared to prior privacy theories, the CI framework is advantageous in identifying potential privacy violations, typically when one or more of the parameters deviate from an established information norm. For example, it might be considered appropriate for a store owner (***recipient***) to collect vaccination information (***attribute***) from a customer (***sender & subjec***t) before letting them into the store (***TP***). However, if the business owner were to use this information for advertising purposes or keep the data indefinitely, the resulting flows, with different TPs, would deviate from the established information norms.

Built upon insights from prior studies leveraging CI to examine the information flows for public health apps [20, 36, 39], **this study rigorously applies the CI framework to examine people's acceptance of COVID mitigation apps in highly diverse contexts.**

Research Questions and Hypotheses

We aim to answer two research questions (RQs) and four specific hypotheses by considering applicable CI parameters and respondents' demographics.

RQ1: What factors impact people's acceptance of sharing data via COVID mitigation apps?

- Null Hypothesis 1.1 (NH1.1): There is no difference in people's acceptance of sharing health data via COVID mitigation apps, even if CI parameters are different.
- Null Hypothesis 1.2 (NH1.2): There is no difference in people's acceptance of sharing data via COVID mitigation apps, even if they have different demographic backgrounds.

RQ2: What factors impact people's acceptance of their data being retained via COVID mitigation apps?

- Null Hypothesis 2.1 (NH2.1): There is no difference in people's acceptance of their data being retained via COVID mitigation apps, even if CI parameters are different.
- Null Hypothesis 2.2 (NH2.1): There is no difference in people's acceptance of their data being retained via COVID mitigation apps, even if they have different demographic backgrounds.

Methods

Variables and measurements

We designed a CI-based survey instrument according to our research question and hypotheses.

The outcome variables are "perceived acceptance", a proxy to measure people's privacy attitudes towards COVID mitigation apps. In RQ1, we use a five-point Likert scale question to capture different acceptance levels because people's privacy preferences are often non-binary [40]. In RQ2, we chose not to specify a retention time due to the evolving COVID guidelines (e.g., how long a person should isolate after getting COVID). Instead, we measure acceptance using a three-level categorical variable to capture necessary nuances.

The independent variables are applicable CI parameters and some demographic features self-reported by respondents. According to CI, it is crucial to include all five CI parameters to comprehensively evaluate the appropriateness of information flow, so we follow a standard CI-based template that includes parameters to construct survey questions (shown in Table 1). We stabilized two CI parameters ([sender] and [subject] are "you" and "your," which refer to the survey respondent), and varied the values of three CI parameters ([attribute], [recipient], and [TP]) as our independent variables.

CI-based Template	Would it be acceptable or unacceptable for [Sender] to share [Subject's] [Attribute] with [Recipient] for [Transmission Principle (TP)]?
Question 1 (Q1)	Via a smartphone mobile app, would it be acceptable or unacceptable for **you** [Sender] to share **your** [Subject's] **recent COVID test result** [Attribute] with **your employer** [Recipient] to work in person [TP]?
Follow-up	Please briefly explain your choice to the previous question (1-2 sentences).
Question 2 (Q2)	In the same scenario above, if **you** [Sender] shared **your** [Subject] **recent COVID test result** [Attribute] via a smartphone mobile app, would it be acceptable or unacceptable for **your employer** [Recipient] to **keep your data** [TP]?
Follow-up	Please briefly explain your choice to the previous question (1-2 sentences).

Table 1: Example questions for one vignette scenario

Survey Design

Vignette surveys are effective to study people's beliefs [41] and to conduct survey-based experiments [42]. This method is widely used in privacy research to capture people's contextual privacy attitudes towards digital technologies [35, 43-46]. We chose the vignette survey method to cover the diverse use cases of COVID mitigation apps in real-world contexts. To craft realistic vignette scenarios, we conducted a technology review of COVID mitigation apps available in the US and gathered news articles about other COVID migration apps deployed around the world. We used the scenarios in our recently published research [anonymous] and slightly modified them to match the scope of this study. Next, we chose a subset of scenarios that would apply to contact tracing, proof of vaccination, and test result reporting apps, and then finalized all the values of the three CI parameters, as shown in Table 2.

CI Parameters	**Values (bold = baseline values in our models)**
Attribute	**(1) Recent COVID test results;** (2) Up-to-date COVID vaccination records; (3) COVID exposure status from phone-based contact tracing;
Recipient	(1) Employers; **(2) Essential stores (grocery stores etc.)**; (3) Non-essential stores (department stores, etc.); (4) Dine-in locations (restaurants, bars, etc.); (5) Large public venues (stadium, music festival, etc.); (6) Healthcare providers (hospitals, clinics, specialists, etc.); (7) Airlines operating international flights; (8) Airlines operating domestic flights; (9) Domestic long-distance transportation operators (trains, greyhound, megabus, etc.); (10) Local public transit operators (subways, metros, commuter trains, buses, etc.)
Transmission Principle (TP)	**(1) Public health purpose;** (2) Scenario-specific purpose (e.g., gain access to [location] or use [service])

Table 2: All CI parameter values in our survey

We then applied a full factorial design across the three CI parameters in Table 2 to generate 60 distinct scenarios. Each scenario contains two main questions corresponding to the two RQs: The first question presents the scenario to gauge acceptance; The second question examines the acceptance toward data retention by the recipient in the scenario. Note that CI considers data retention as a type of TP, so both questions conform to the standard CI-based template.

Survey Questionnaire and Study Ethics

The survey questionnaire began with a consent page, which confirmed participant eligibility and obtained informed consent. Then, the questionnaire displayed two information pages, including plain language definitions of COVID-related terminology and examples of some COVID mitigation apps deployed in the US. At the end of the information pages, we asked respondents to confirm their understanding of the information. Failure to confirm did not disqualify respondents. but their responses were excluded from data analysis.

Afterwards, the questionnaire displayed 10 randomly selected vignette scenarios to limit the study time to around 10 minutes to minimize survey fatigue [47]. As shown in Table 1, each scenario has two CI-based questions. In 2 out of 10 vignette scenarios, we inserted two follow-up free-text questions to gather additional qualitative data to understand respondents' rationale. Finally, the questionnaire ended with a set of culturally responsible demographic questions for the US population and additional background questions on their COVID experience.

For attention check, we avoided conventional attention check questions that are irrelevant to the survey because they are ineffective and may undermine researcher-participant trust [48]. Instead, we used multiple metrics as attention and accuracy checks, including the time spent on each scenario and the quality of free-text responses.

Recruitment and Data Collection

This survey study was approved by the Institutional Review Board (IRB) at the first author's institution. The IRB-approved survey questionnaire was implemented in Qualtrics for online distribution. We chose the Prolific research platform [49] to recruit respondents for its data collection speed and quality. We ran three small pilot surveys in December 2022 and January 2023, which led to minor refinement of the questionnaire. Next, we distributed the finalized survey in February 2023 and recruited a US representative sample via Prolific [50]. We received 694 completed survey responses and excluded two responses due to obvious survey abuse. The remaining 692 survey respondents were each compensated $2 for their time (average compensation rate = $10.43/hour).

We performed a two-step data cleaning procedure using a customized Python script, followed by manual inspection. This led to the exclusion of 18 responses due to the lack of substance in the free-text answers (n=12) and the nonsensical content of the free-text answers (n=6). We included the remaining 674 survey responses in the final analysis.

Statistical Analysis

Because our outcome variables for both RQs are ordinal data, **multilevel ordered logistic regression** is suitable to examine the effects of multiple predators. We used the cumulative link mixed models (clmm) in the ordinal package in R [51] with random effects to account for repeated measures in the survey.

We selected the most promising variables as predictors to construct our models, as follows:

Main effect predictors: We include all values of *attribute*, *recipient*, and *TP*, as well as six demographic variables (age, gender, political leaning, living areas, education, and income), and four COVID experience questions (installation of contact tracing apps, being tested positive for COVID, being vaccinated against COVID, and knowing someone who got seriously ill or passed away from COVID) as main effect predictors.

Effect modifiers: We account for the interactions among CI parameters by including effect modifications to the estimates of individual main effects. We include all pairwise combinations of the three CI parameters (i.e., *attribute * recipient, recipient * TP, and TP * attribute*) as effect modifiers in our models. These effect modifiers enable us to interpret special cases when two specific CI parameters are present.

Predictor baselines: For each predictor and effect modifier, we set the baseline value to the most common option according to the US population's familiarity. For example, we chose COVID test results as the baseline for Attribute because app-based contact tracing and digital vaccination records were less commonly adopted in the US. The baseline values for CI parameters are bolded in Table 1.

Final models: We constructed two ordered logistic regression models for two RQs, respectively. Our models are inherently complex due to the large number of main effect predictors and effect modifiers. To ensure model convergence, we combined data categories in some demographic variables (e.g., age groups, political leaning) to reduce model complexity. We also converted "not sure" and "prefer not to answer" responses to the "not available (N/A)" placeholder value to maximize model convergence. Our models used the "ucminf" optimizer in place of the package default optimizer “nlminb”. Both are commonly used optimizer algorithms to maximize the marginal likelihood function.

Results Reporting and Interpretation

We followed the best practices outlined in [52] to report and interpret our model results. For statistically significant predictors ($p<0.05$), we reported the odds ratios (OR) of the effect, where OR is the natural exponent of the model estimate (β) for a predictor. We also report the 95% confidence intervals (95% CI) of ORs. Tables 3 and 4 are the model coefficients tables for Q1 and Q2, respectively.

For main effect interpretation, if a predictor value has an OR of 2, it means respondents are twice as likely to accept the scenario when compared to the baseline value of the predictor. To interpret the interactions among two CI parameters, we must calculate the marginal ORs of the main effect predictors and effect modifiers using the formula: $e^\wedge(\beta_{main\_effect\_predictor}+\beta_{effect\_modifier})$. For example, if the estimate for a main effect predictor value is 2 (OR=7.39), and the estimate of the effect modifier containing a second predictor value is 0.5, then the marginal OR is e^(2+0.5)=12.18. This means the presence of the second predictor value increased the OR of the main effect predictor value from 7.39 to 12.18 compared to the main effect predictor baseline value. We also calculated the marginal 95% confidence intervals for these interactions.

Each participant answered free-text questions for two randomly selected scenarios. After excluding low-quality free-text responses, we collected 2679 responses in total: 1340 for Q1 (44.7 per scenario) and 1339 for Q2 (44.6 per scenario). We performed a simplified qualitative analysis to synthesize notable themes from these responses, and then selected representative quotes to further explain or support our statistical results.

Results

Respondents and Descriptive Statistics

We recruited a simple US representative sample (N=674) via Prolific that resembles US Census data across age, gender, and race/ethnicity (see Appendix). We present the overall descriptive statistics of

Q1 and Q2 responses in Figures 1 to 6.

Figures 1-3 depicts respondents' acceptance levels for sharing their data via COVID mitigation apps in all the vignette scenarios. Generally, data sharing is mostly acceptable, as respondents found data sharing "acceptable" or "somewhat acceptable" in 61.5% of all scenarios (4147/6740, referred to as "overall acceptance" thereafter). Across all attributes, sharing is most acceptable when recipients are healthcare providers (82%, 538/657), employers (70%, 484/692), and airlines operating international flights (76%, 515/675). Regarding attributes, respondents were less comfortable sharing COVID exposure status from contact tracing (58% overall acceptance, 1284/2233) than sharing vaccination records (63% overall acceptance, 1435/2283) or test results (64% overall acceptance, 1428/2224).

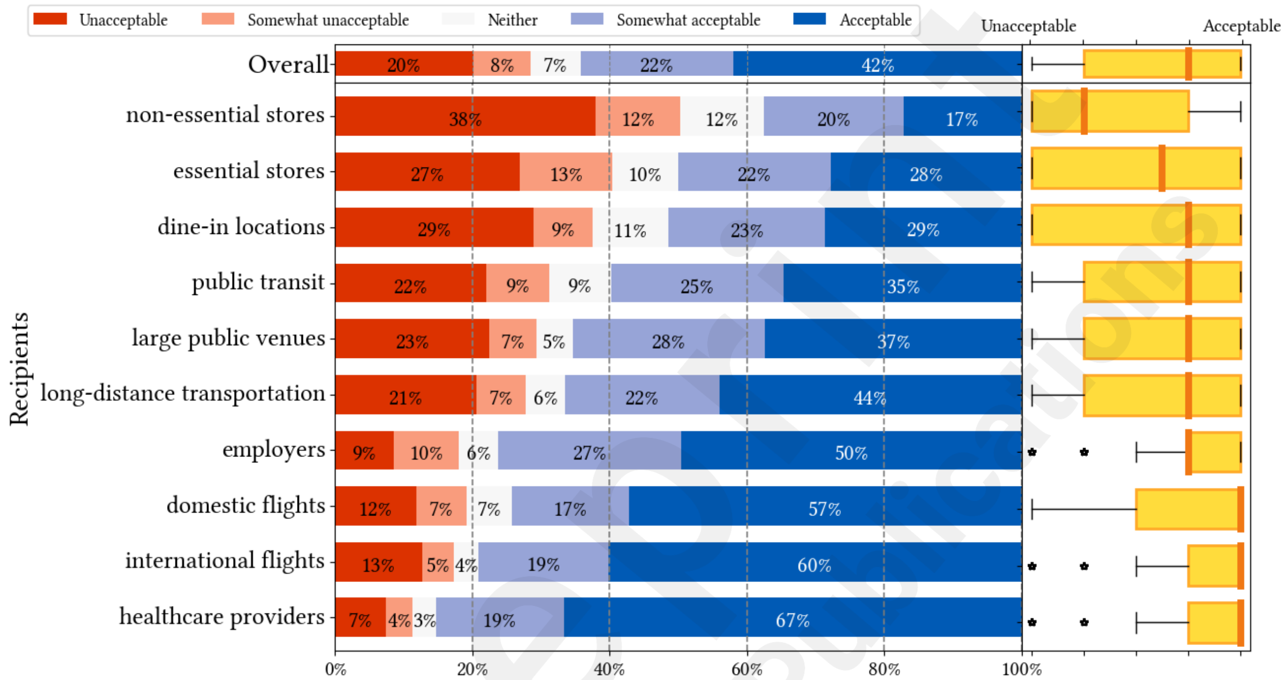

Figure 1: Descriptive statistics of Q1 responses: Acceptance of sharing recent COVID test results in different vignette scenarios, organized by recipients.

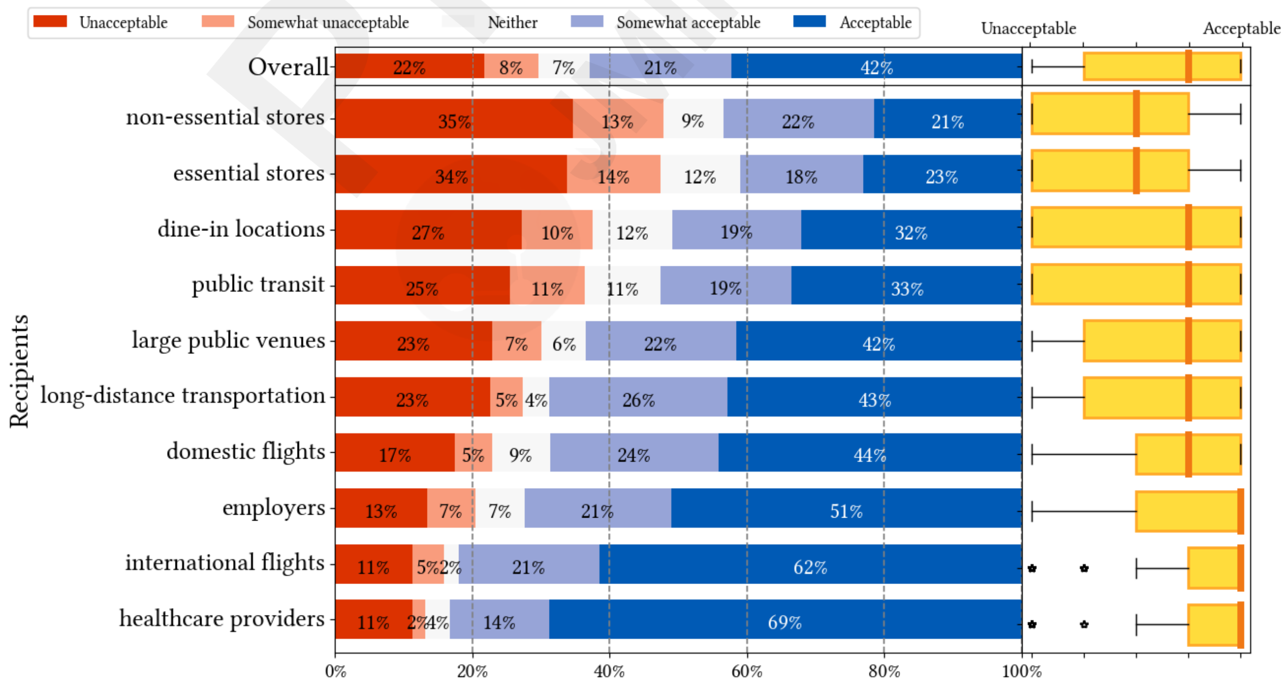

Figure 2: Descriptive statistics of Q1 responses: Acceptance of sharing up-to-date COVID

vaccination records in different vignette scenarios, organized by recipients.

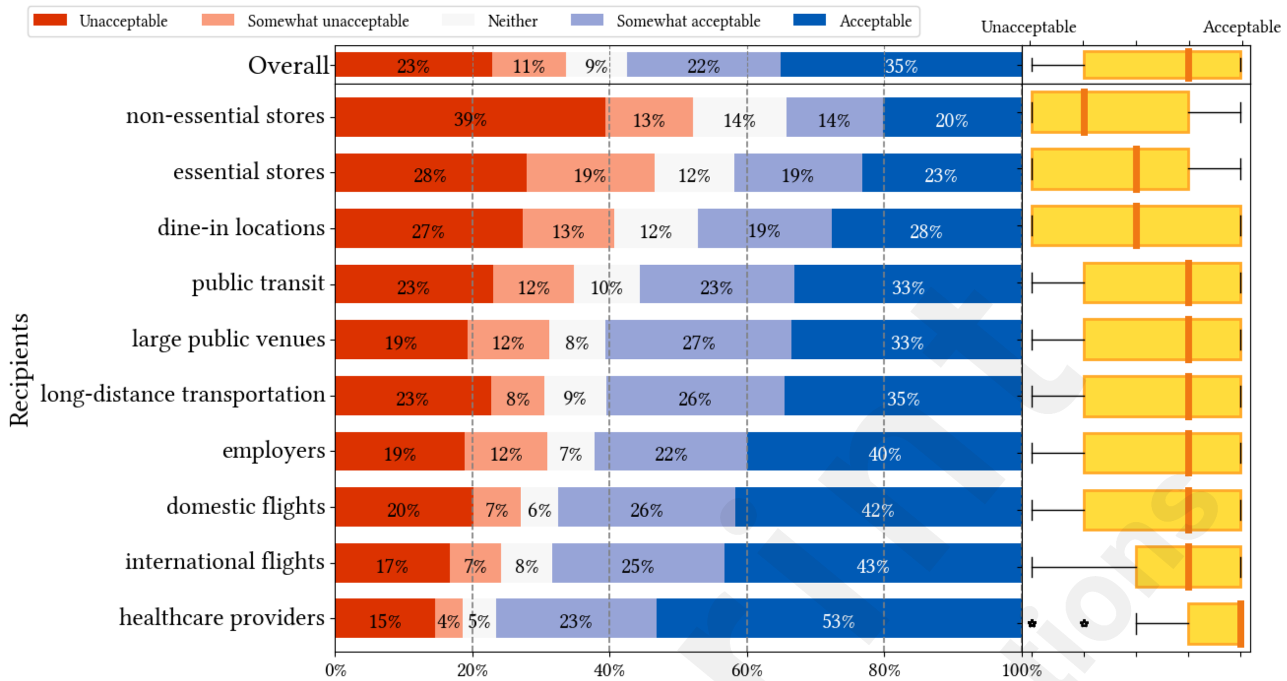

Figure 3Descriptive statistics of Q1 responses: Acceptance of sharing COVID exposure status from phone-based contact tracing in different vignette scenarios, organized by recipients.

Figures 4-6 shows respondents' acceptance levels for their health data being retained by recipients in all vignette scenarios. Across all attributes and recipients, considerable numbers of respondents felt data retention was "unacceptable" (44% of all scenarios, 2947/6740) or "acceptable, only for a limited amount of time" (45% of all scenarios, 3010/6740). Only in 11% of all scenarios (783/6740), respondents reported recipients retaining their health data as "acceptable, no matter how long it will be kept" (or acceptable without a time limit). Across all recipients, healthcare providers retaining health data is most accepted, but only in 37% of healthcare provider scenarios (244/657) respondents felt data retention was acceptable without a time limit. Similarly, small percentages of respondents found data retention without a time limit acceptable across all attributes: 10% (214/2233) of scenarios for contact tracing exposure status, 14% (314/2283) of scenarios for vaccination records, and 11% (255/2224) of scenarios for test results (11%, 255/2224), respectively. The only outliner is healthcare providers retaining vaccination records, where 47% (103/221) responses to this scenario were acceptable without a time limit. Overall, Q2 results are largely consistent with Q1 results in terms of recipients, while **retention time** differentiates respondents' acceptance levels drastically.

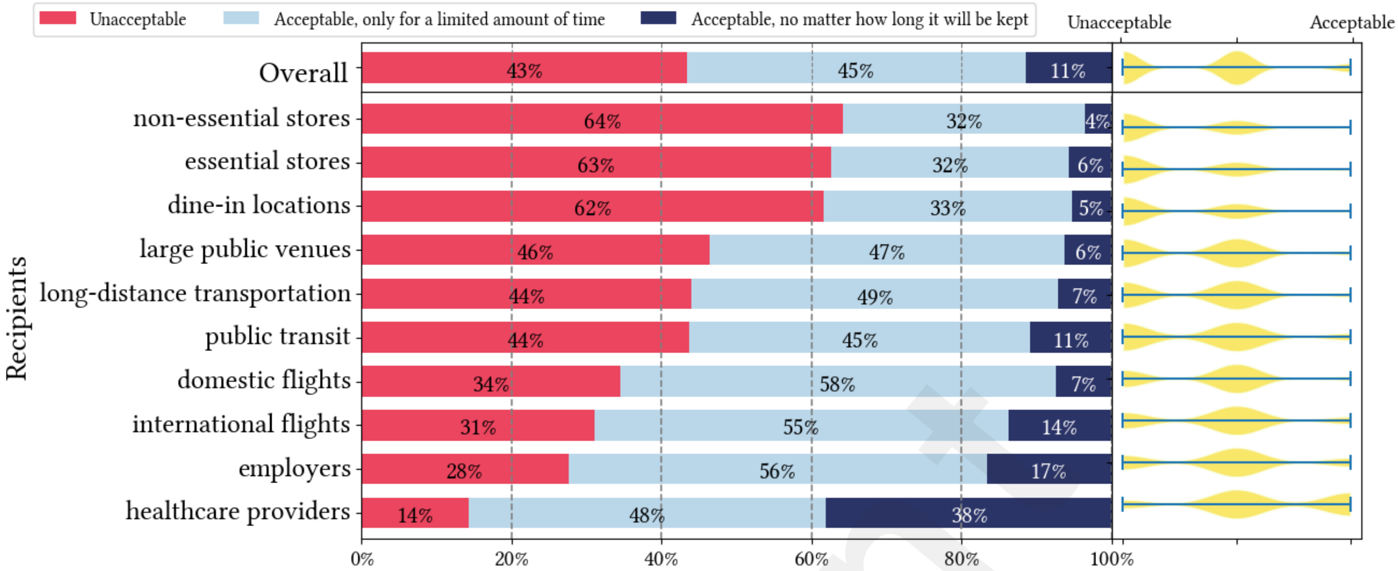

Figure 4: Descriptive statistics of Q2 responses: Acceptance of recent COVID test results being retained in different vignette scenarios, organized by recipients.

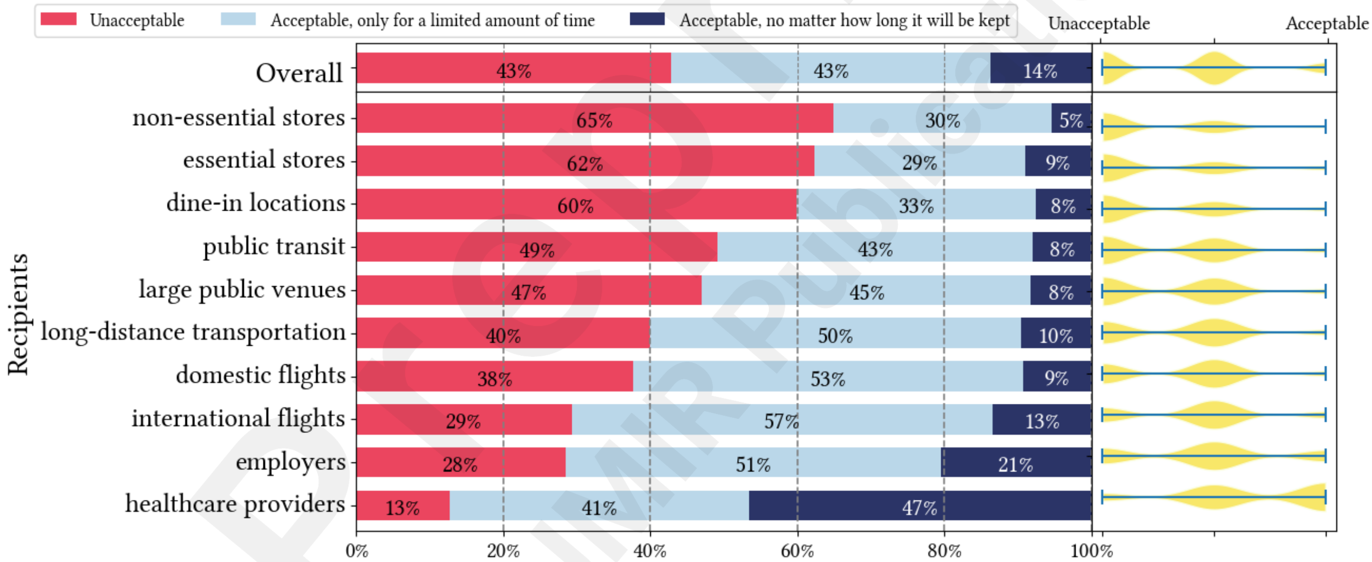

Figure 5: Descriptive statistics of Q2 responses: Acceptance of up-to-date COVID vaccination records being retained in different vignette scenarios, organized by recipients.

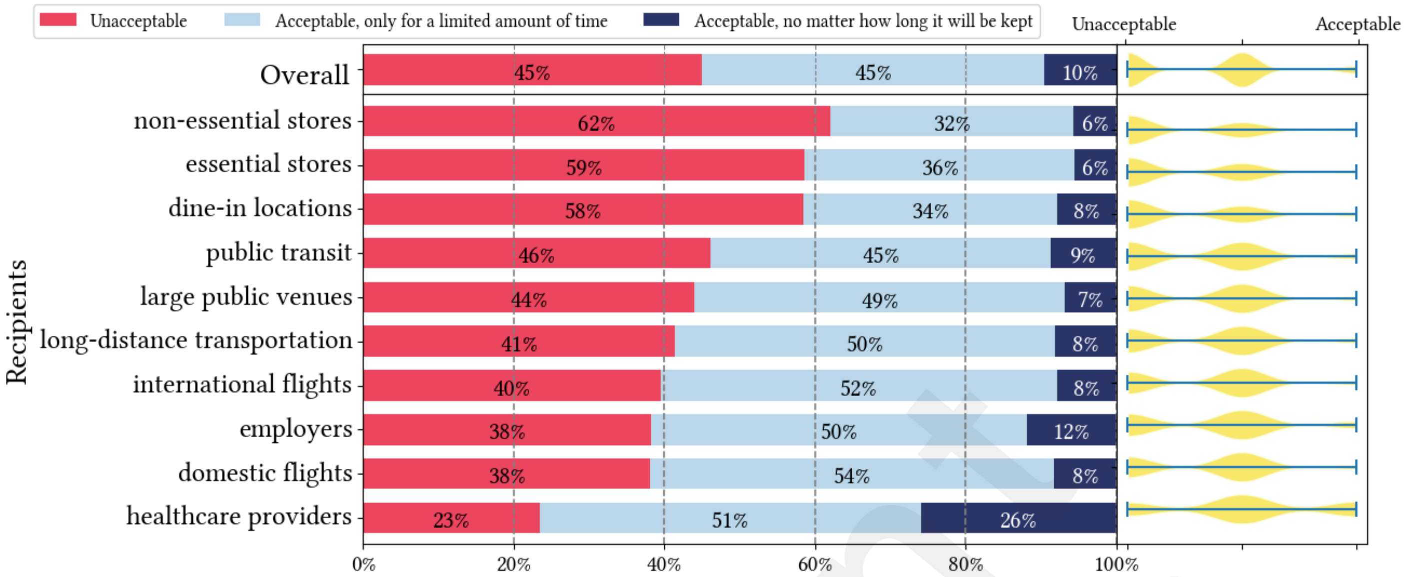

Figure 6: Descriptive statistics of Q2 responses: Acceptance of COVID contact tracing exposure status being retained in different vignette scenarios, organized by recipients.

RQ1: Acceptance of data sharing through COVID mitigation apps

Predictors and Effect Modifiers	Estimate β	Odds Ratio	95% Confidence Interval	p-value
Attribute				
test results	0.00	1.00	—	
exposure status	0.07	1.08	0.68-1.72	.76
vaccination records	-0.17	0.84	0.53-1.34	.47
Transmission Principles (TP)				
public health	0.00	1.00	—	
scenario-specific	0.08	1.09	0.73-1.62	.69
Recipient				
essential stores	0.00	1.00	—	
dine-in locations	0.28	1.32	0.80-2.21	.28
domestic flights	2.42	11.34	6.53-19.68	**<.001**
employers	2.39	10.94	6.37-18.78	**<.001**
healthcare providers	4.98	146.36	78.09-274.32	**<.001**
international flights	2.77	16.03	8.88-28.92	**<.001**
large public venues	1.41	4.13	2.45-6.97	**<.001**
long-distance transportation	1.77	5.87	3.42-10.09	**<.001**
non-essential stores	-1.05	0.35	0.21-0.59	**<.001**
public transit	1.13	3.12	1.84-5.27	**<.001**
Attribute * Recipient				
exposure status * dine-in locations	0.18	1.21	0.65-2.25	.56
vaccination records * dine-in locations	0.40	1.50	0.80-2.79	.21
exposure status * domestic flights	-0.40	0.68	0.35-1.30	.24
vaccination records * domestic flights	0.15	1.16	0.61-2.21	.64
exposure status * employers	-0.61	0.54	0.29v1.04	.065
vaccination records * employers	0.55	1.75	0.91-3.36	.095
exposure status * healthcare providers	-1.64	0.20	0.10-0.40	**<.001**
vaccination records * healthcare providers	-0.30	0.74	0.35-1.57	.44
exposure status * international flights	-0.85	0.43	0.22-0.85	**.015**
vaccination records * international flights	0.35	1.43	0.71-2.88	.32
exposure status * large public venues	-0.27	0.77	0.41-1.46	.42
vaccination records * large public venues	0.01	1.01	0.54-1.91	.97
exposure status * long-distance transportation	-0.58	0.56	0.29-1.08	.085
vaccination records * long-distance transportation	0.12	1.13	0.58-2.18	.72
exposure status * non-essential stores	0.17	1.20	0.63-2.28	.59
vaccination records * non-essential stores	0.32	1.39	0.73-2.62	.32
exposure status * public transit	-0.14	0.87	0.46-1.64	.67

Predictors and Effect Modifiers	**Estimate β**	**Odds Ratio**	**95% Confidence Interval**	**p-value**
vaccination records * public transit	0.18	1.20	0.65-2.24	.56
Attribute * TP				
exposure status * scenario-specific	-0.39	0.68	0.51-0.92	**.012**
vaccination records * scenario-specific	-0.29	0.75	0.55-1.01	.062
TP * Recipient				
scenario-specific * dine-in locations	-0.02	0.98	0.59-1.63	.94
scenario-specific * domestic flights	0.02	1.02	0.60-1.73	.94
scenario-specific * employers	0.06	1.07	0.63-1.81	.81
scenario-specific * healthcare providers	-0.53	0.59	0.33-1.07	.080
scenario-specific * international flights	0.54	1.72	0.99-2.98	.052
scenario-specific * large public venues	-0.02	0.99	0.59-1.67	.97
scenario-specific * long-distance transportation	-0.05	0.96	0.56-1.64	.88
scenario-specific * non-essential stores	0.38	1.46	0.86-2.47	.16
scenario-specific * public transit	0.01	1.02	0.61-1.71	.94
Gender				
Female	0.00	1.00	—	
Male	-0.17	0.85	0.48-1.50	.57
Non-binary	-0.09	0.92	0.12-7.06	.94
Age				
60+	0.00	1.00	—	
18-29	0.16	1.18	0.48-2.88	.72
30-39	0.13	1.14	0.47-2.81	.77
40-49	0.55	1.75	0.70-4.34	.23
50-59	-0.20	0.82	0.35-1.90	.64
Politics				
Moderate	0.00	1.00	—	
Conservative	-0.79	0.46	0.20-1.03	.059
Liberal	1.57	4.85	2.45-9.61	**<.001**
Living Area				
Town or suburb	0.00	1.00	—	
City	0.25	1.30	0.71-2.39	.40
Rural area	0.44	1.55	0.65-3.72	.32
Education				
High school	0.00	1.00	—	
College	-0.76	0.47	0.21-1.08	.074
Grad School	-0.30	0.75	0.26-2.18	.59
Income				
$50,000 - $99,999	0.00	1.00	—	
$25,000 - $49,999	0.22	1.26	0.59-2.67	.55

Predictors and Effect Modifiers	Estimate β	Odds Ratio	95% Confidence Interval	p-value
Less than $25,000	0.52	1.68	0.72-3.93	.28
More than $100,000	0.64	1.91	0.89-4.12	.096
COVID Test				
No	0.00	1.00	—	
Yes	0.39	1.48	0.82-2.66	.19
COVID App				
No	0.00	1.00	—	
Yes	1.61	5.01	2.34-10.73	**<.001**
COVID Vaccination				
No	0.00	1.00	—	
Yes	2.35	10.54	4.93-22.55	**<.001**
COVID Illness				
No	0.00	1.00	—	
Yes	0.54	1.72	0.98-3.03	.060

Table 3: RQ1 model coefficients table with all main effect predictors and effect modifiers

CI parameters

***Recipient* is the most powerful CI parameter to predict respondents' acceptance levels towards COVID mitigation apps.** The recipients with the largest effects were healthcare providers (OR=146.36, 95%CI=78.06-274.42, p<0.001), employers (OR=10.94, 95%CI=6.37-18.78, p<0.001), and airlines operating domestic (OR=11.34, 95%CI=6.53-19.69) and international flights (OR=16.03, 95%CI=8.88-28.93, p<0.001), where respondents were more willing to use mobile apps to share their personal health information with them compared to the baseline recipient of essential stores. Respondents' free text responses revealed that the most accepted recipients are in scenarios that could critically impact the health of others and themselves. For example, respondents commented that sharing data with health providers "is necessary to keep track of the virus…also necessary to keep myself and others healthy," sharing data with airlines "would help keep travelers safe," and sharing with employers "is important for my coworkers to feel safe when I come to work."

Additionally, large public venues (OR=4.13, 95%CI=2.45-6.97, p<0.001), local public transit operators (OR=3.12, 95%CI=1.84-5.27, p<0.001), and long-distance transportation operators (OR=5.87, 95%CI=3.42-10.09, p<0.001) were also more tolerated than the baseline. In contrast, sharing data via mobile apps with non-essential stores (OR=0.35, 95%CI=0.21-0.59, p<0.001) was less accepted than the baseline. Respondents' comments explained the reasons: "Non-essential stores do not need this data," "That's too drastic. You can't deny people access to food and supplies." Only **dine-in locations** had a non-statistically significant effect.

However, no *attribute* or *TP* value has a significant effect. Respondents did not report significant differences in acceptance levels towards sharing contact tracing exposure status or proof of vaccination from test results. Similarly, scenario-specific purposes are not statistically different from the generic public health purposes. Note that we group all scenario-specific purposes into one TP value to ensure model convergence, which means our model may miss some TP nuances in specific scenarios.

Interactions among CI parameters

Our model reveals notable interactions among CI parameters, where some combinations of two CI parameter values yield worth-noting results in certain special cases.

When considering *recipient* and *attribute* values pairwise, although respondents are willing to share their health information across all attributes with healthcare providers, the OR dropped from 146.36 to 28.22 when the attribute is contact tracing exposure status (marginal OR=28.22, 95%CI=11.57-68.84, p<0.001). There was a similar drop in OR when sharing contact tracing exposure status with airlines operating international flights (marginal OR=6.82, 95%C=2.85-16.32, p=0.015). In the free-text responses of these secnarios, most respondents expressed that sharing exposure status was useful to keep healthcare facilities and other passengers safe, but a few doubted its necessity at the late stage of this pandemic since “now we have vaccines.” This qualitative data indicates **relatively low acceptance of sharing contact tracing exposure status via mobile apps when other effective pandemic mitigation measures are avaialable, even with the most acceptable recipients.**

The combination of *attribute* and *TP* values shows that respondents are slightly less likely to share contract tracing exposure status than test results (marginal OR=0.73, 95%CI=0.71-0.75, p=0.012) when TP is scenario-specific purposes(e.g., entering a place or using a service). Many comments pointed out the questionable accuracy of phone-based contact tracing exposure status,as one respondent wrote: “I don't trust the standards developed to determine exposure, I don't trust the network designed to measure exposure, and I don't trust the data on the other end of the transaction (others I might have been exposed to).” **This qualitative data further supports respondents’ overall reluctance to share contact tracing data, especially for non-public health purposes.**

Demographics and COVID experiences

Political leaning is the only statistically significant demographic predictor. Compared to self-identified political moderates, self-identified liberals (OR=4.85, 95%CI=2.44-9.61, p<0.001) are more likely to accept using COVID mitigation apps. Age, living areas, education, and income did not significantly affect respondents' acceptance levels. Interestingly, some prior COVID experiences also turned out to be significant. Respondents who have installed COVID contact tracing apps (OR=5.01, 95%CI=2.34-10.73, p<0.001) and who have received COVID vaccination (OR=10.54, 95%CI=4.92-22.56, p<0.001) were generally more acceptable about data sharing via COVID mitigation apps. **These indicate that people’s familiarity with COVID mitigation apps and their attitude towards vaccination may play a role in their acceptance of COVID mitigation apps.**

RQ2: Acceptance of data retention through COVID mitigation apps

Predictors and Effect Modifiers	Estimate, β	Odds Ratio	95% Confidence Interval	p-value
Attribute				
test results	0.00	1.00	—	
exposure status	0.45	1.57	1.56-1.58	**<.001**
vaccination records	0.52	1.69	1.68-1.70	**<.001**
Recipient				
essential stores	0.00	1.00	—	
dine-in locations	0.53	1.71	1.15-2.54	**0.008**
domestic flights	2.25	9.50	9.45-9.55	**<.001**
employers	3.19	24.34	24.21-24.48	**<.001**
healthcare providers	5.52	251.77	172.17-368.16	**<.001**
international flights	2.79	16.36	10.89-24.57	**<.001**
large public venues	1.36	3.93	2.66-5.81	**<.001**
long-distance transportation	2.03	7.67	5.08-11.59	**<.001**
non-essential stores	0.17	1.20	1.19-1.20	**<.001**
public transit	1.78	5.96	5.92-5.99	**<.001**
Attribute * Recipient				
exposure status * dine-in locations	-0.28	0.76	0.44-1.31	0.32
vaccination records * dine-in locations	-0.37	0.69	0.40-1.19	0.19
exposure status * domestic flights	-0.55	0.58	0.58-0.58	**<.001**
vaccination records * domestic flights	-0.18	0.84	0.58-1.21	0.35
exposure status * employers	-1.38	0.25	0.25-0.25	**<.001**
vaccination records * employers	-0.06	0.95	0.94-0.95	**<.001**
exposure status * healthcare providers	-1.63	0.20	0.12-0.33	**<.001**
vaccination records * healthcare providers	-0.01	1.00	0.59-1.69	0.99
exposure status * international flights	-0.95	0.39	0.23-0.66	**<.001**
vaccination records * international flights	-0.35	0.71	0.42-1.20	0.20
exposure status * large public venues	-0.28	0.76	0.45-1.29	0.31
vaccination records * large public venues	-0.55	0.58	0.34, 0.98	**0.043**
exposure status * long-distance transportation	-0.77	0.47	0.27, 0.82	**0.008**
vaccination records * long-distance transportation	-0.34	0.71	0.41-1.24	0.23
exposure status * non-essential stores	-0.26	0.77	0.77-0.78	**<.001**

Predictors and Effect Modifiers	Estimate, β	Odds Ratio	95% Confidence Interval	p-value
vaccination records * non-essential stores	-0.62	0.54	0.35-0.83	**0.005**
exposure status * public transit	-0.53	0.59	0.59-0.59	**<.001**
vaccination records * public transit	-0.62	0.54	0.37-0.79	**0.001**
Gender				
Female	0.00	1.00	—	
Male	0.15	1.17	0.72-1.89	0.53
Non-binary	0.64	1.91	0.33-11.04	0.47
Age				
60+	0.00	1.00	—	
18-29	0.60	1.82	0.95-3.50	0.070
30-39	0.02	1.03	1.02-1.03	**<.001**
40-49	0.50	1.65	0.82-3.32	0.16
50-59	-0.18	0.84	0.44-1.57	0.58
Politics				
Moderate	0.00	1.00	—	
Conservative	-0.50	0.61	0.33-1.12	0.11
Liberal	0.70	2.03	2.01-2.04	**<.001**
Living				
Town or suburb	0.00	1.00	—	
City	-0.10	0.91	0.54-1.52	0.71
Rural area	0.05	1.06	0.50-2.25	0.88
Education				
High school	0.00	1.00	—	
College	-0.26	0.77	0.77-0.78	**<.001**
Grad School	0.16	1.18	0.60-2.29	0.64
Income				
$50,000 - $99,999	0.00	1.00	—	
$25,000 - $49,999	-0.01	0.99	0.99-1.00	**0.003**
Less than $25,000	-0.15	0.87	0.46-1.63	0.66
More than $100,000	-0.02	0.98	0.54-1.80	0.96
COVID Test				
No	0.00	1.00	—	
Yes	0.14	1.16	0.70-1.91	0.57
COVID App				
No	0.00	1.00	—	
Yes	1.22	3.39	1.77-6.48	**<.001**
COVID Vaccination				
No	0.00	1.00	—	

Predictors and Effect Modifiers	Estimate, β	Odds Ratio	95% Confidence Interval	p-value
Yes	1.55	4.74	4.71-4.77	**<.001**
COVID Illness				
No	0.00	1.00	—	
Yes	0.60	1.84	1.16-2.90	**0.009**

Table 4: RQ2 model coefficients table with all main effect predictors and effect modifiers

CI parameters

We included two CI parameters (*recipient* and *attribute*) as predictors in the Q2 model because data retention practices are considered TP. *Recipient* remains the most impactful CI parameter for respondents' acceptance of data retention by COVID mitigation apps. Compared to the baseline of essential stores, all other recipients are more accepted if they retain respondents' health data from various COVID mitigation apps. The largest effect remains in healthcare providers (OR=251.77, 95%CI=172.17-368.16, p<0.001), followed by employers (OR=24.34, 95%CI=24.21-24.48, p<0.001) and airlines operating international flights (OR=16.36, 95%CI=10.89-24.57, p<0.001). These results resemble those of RQ1, showing that respondents' acceptance of data retention practices primarily depends on recipients. **Notably, the free-text responses reveal nuanced opinions on retention time.** For example, even with the most accepted *recipient* healthcare providers, one respondent felt sharing test results was "only acceptable for the duration of the medical treatment," and another commented on retaining exposure status: "After a point, it will become outdated and useless, and should be deleted for privacy reasons." This qualitative data suggests that the acceptance of data retention practices are associated with the necessity of specific scenarios.

Regarding *attribute*, respondents expressed slightly greater acceptance of having their vaccination records (OR=1.69, 95%CI=1.68-1.70, p<0.001) and their contact tracing exposure status (OR=1.57, 95%CI=1.56-1.58, p<0.001) retained by recipients compared to the baseline of COVID test results, **which differs from RQ1 results.** However, the effect is small and there were no notable themes in the free-text responses to clearly explain such differences.

Interactions among CI parameters

Many combinations of *attribute* and *recipient* values show that respondents' acceptance of data retention through COVID mitigation apps dropped significantly, **demonstrating the potential inappropriateness for certain recipients to retain their phone-based contact tracing exposure status and their vaccination records.**

When *attribute* is phone-based contact tracing exposure status, respondents' acceptance of data retention significantly decreased for seven out of ten recipients, with the largest drop in the most accepted recipients including healthcare providers (marginal OR=48.91, marginal 95%CI=29.04-82.41, p<0.001), employers (marginal OR=6.11, marginal 95%CI=3.64-10.25, p<0.001), airliners operating international flights (marginal OR=6.82, marginal 95%CI=3.72-11.56, p<0.001). In the free-text responses, one respondent found it acceptable for employers to retain exposure status data when "the virus was transmittable," while another believed exposure status "is not needed now in 2023" for air travel. There are smaller acceptance decreases for airlines operating domestic flights (marginal OR=5.47, marginal 95%CI=3.22-9.29, p<0.001), long-distance transportation operators (marginal OR=3.53, marginal 95%CI=2.02-6.16, p=0.008), and local public transit operators (marginal OR=3.49, marginal 95%CI=2.05-5.95, p<0.001). Notably, the acceptance of non-essential stores retaining data (marginal OR=0.91, marginal 95%CI=0.52-1.62, p<0.001) dropped even below that of the baseline as one respondent commented: “I don't see the need for non-essential stores to keep my private data.” **These results resonate with RQ1: people were less comfortable with data practices around phone-based contact tracing data due to lack of necessity.**

When *attribute* is COVID vaccination records, data retention acceptance decreased for four recipients, with large drops for local public transit operators (marginal OR=3.19, marginal 95%CI=1.89-5.38, p=0.001), large public venues (marginal OR=2.25, marginal 95%CI=1.32-3.82, p=0.043), non-essential stores (marginal OR=0.64, marginal 95%CI=0.36-1.12, p=0.005), and a small drop for employers (marginal OR=22.87, marginal 95%CI=13.80-37.92, p<0.001). The free-text responses revealed that many respondents believed vaccination records were medical records and “shouldn’t be disclosed and even less stored or kept.” Others worried about potential data breaches after data retention that “leaked information about a person's medical history and choices.” Another respondent found it acceptable for large public venues to keep it but “it should be deleted after the event has ended and resubmitted for every event.” **This qualitative evidence suggests the inappropriateness for some everyday services and venues to retain people's vaccination records due to the medical nature of the data.**

Demographics and COVID experiences

Several demographic predictors have significant effects in the Q2 model. Similar to Q1, self-identified liberals (OR=2.03, 95%CI=2.01-2.04, p<0.001) are slightly more likely to accept recipients to retain their health data via a mobile app. We also observe a significant but small effect for respondents aged 30 to 39 (OR=1.03, 95% CI=1.02-1.03, p<0.001) compared to those aged 60 and plus. In the opposite direction, compared to those with high school education, respondents with college education are less acceptable towards data retention practices (OR=0.77, 95%CI=0.77-0.78, p<0.001). Similarly, we found a significant but smaller effect for respondents with self-reported annual income of $25,000 to $49,999 (OR=0.99, 95% CI=0.99-1.00, p=0.003) compared to those with self-reported annual income of $50,000 to $99,999. Regarding COVID experiences, Respondents who have installed COVID contact tracing apps (OR=3.39, 95%CI=1.77-6.48, p<0.001), who have received COVID vaccination (OR=4.74, 95%CI=4.71-4.77, p<0.001), and who knew someone who got seriously ill or passed away (OR=1.84, 95%CI=1.16-2.90, p=0.009) are more likely to accept data retention practices by various recipients.

Summary of Results

For RQ1, we discovered that the CI parameter *recipient* has the most significant effect on how willing respondents are to share data through COVID mitigation apps, and that certain combinations of *recipient*, *attribute,* and *TP* values also influence their willingness. These results, taken together, reject NH1.1. Among demographic variables, self-reported political leaning and prior COVID experiences impact respondents’ overall acceptance, rejecting NH1.2.

For RQ2, the CI parameter *recipient* greatly influences respondents' acceptance of data retention practices via COVID mitigation apps. The CI parameter *attributes* also turned out to be significant, as respondents felt that retaining their COVID test results was less acceptable. Moreover, many combinations of *attribute* and *recipient* values further impact respondents’ acceptance of data retention practices via COVID mitigation apps. These results, taken together, reject NH2.1. Regarding demographics, besides respondents’ political leaning and prior COVID experiences as in RQ1 results, age, self-reported education, and annual income also have significant effects on respondents’ acceptance of data retention, thereby rejecting NH2.2.

Discussion

Contributions of this Study

By surveying an online US representative sample, this study confirms prior research that data privacy is a key factor impacting the adoption of COVID mitigation apps [3, 9-10, 20, 24-25], and that the specific contexts impact people's privacy attitudes towards these apps [20, 36, 39].

Different from prior studies that only examined user-centered data privacy for one type of COVID mitigation apps [3, 9-10, 26-27], our study revealed US respondents' varying acceptance of different types of COVID mitigation apps that collect different types of personal health data. This highlights the importance of holistically examining multiple COVID mitigation apps after the pandemic dust settles, providing insights into the deployment of different types of pandemic mitigation apps to combat future public health crises.

Besides exploring the general acceptance of sharing personal health data via COVID mitigation apps, this study dived into people's attitudes towards data retention practices via these apps – a critical consideration in privacy research [28-30]. In many scenarios, we found US respondents' acceptance differed from their acceptance of initial data sharing, highlighting the importance of thoroughly considering public health mobile apps' data retention practices.

Finally, this study contributes to the broader application of the CI privacy framework to analyze how contextual data privacy impacts the acceptance of COVID mitigation apps, showing the framework's suitability to gauge people's acceptance of pandemic mitigation apps and other public health technologies.

Limitations and Future Research

We acknowledge several limitations of the study and suggest future research directions. First, this study inherits the limitations of the online survey methodology, where we relied on respondents' self-reported data. We mitigated this by focusing on respondents' self-reported attitudes and, rather than using attitudes to predict actual behaviors. Future research could explore data on people's actual behaviors with COVID mitigation apps to triangulate our study findings.

Second, we minimized the survey sampling bias by recruiting a US representative sample on Prolific. Still, our findings cannot fully represent the US population's perspective or generalize beyond the US. To provide comparative analyses, we encourage researchers to replicate our CI-based survey methods to examine people's acceptance of COVID mitigation apps in other countries or regions. This will elucidate potentially different CI information norms regarding pandemic mitigation apps across cultures.

Third, though this survey depicts US respondents' contextual acceptance of various COVID mitigation apps at the end of the pandemic, it does not show longitudinal trends about people's privacy attitudes towards these apps. However, researchers can quickly adjust and deploy the CI-based survey methods developed in this study longitudinally, should future public health research needs arise. This way, future research could generate longitudinal insights into the acceptance of public health technologies using a consitent CI-based survey instrument.

Furthermore, we only evaluated the most important set of contextual factors according to the CI framework and the app types being examined, due to the quantitative nature of the survey and the goal of generating meaningful statistical results. Also, though the qualitative data collected from the free-text questions enhanced our statistical results, the short survey completion time limited the depth of such data. We encourage researchers to explore a richer set of contextual factors and consider alternative research methods to generate deeper qualitative findings. Deployment Strategies for Future Pandemic Mitigation Apps

This study provides a cross-sectional overview of people's contextual acceptance of three major types of COVID mitigation apps post-pandemic in the US, which informs the deployment strategies for future pandemic mitigation apps.Our results backed up prior CI-inspired studies [20, 36, 39] that CI parameters, especially *recipient, attribute*, and *TP*, can predict people's acceptance of COVID mitigation apps in different situations. This survey's fully factorial design enabled us to extend these prior studies by investigating interactions among CI parameters. We found the *recipient* to be the most influential CI parameter, while the interplay among multiple CI parameters in specific scenarios complicated people's acceptance levels. This implies that there are no one-size-fits-all data privacy norms for COVID mitigation apps, and that the specific contexts for data practices, often determined by a combination of CI parameters, matter. In the case of a future pandemic, we recommend public health policymakers proactively collect evidence-based data about the general public's contextual acceptance of using various pandemic mitigation apps to inform their decisions on when, where, and how to deploy these apps.

Our statistical models for both RQs revealed that political leaning and prior COVID experiences also influenced people's acceptance of COVID mitigation apps. Specifically, respondents who self-identified as liberals, have downloaded COVID mitigation apps, and have been vaccinated against COVID-19, generally reported higher acceptance levels. The RQ2 model also yielded a few significant demographic predictors (e.g., age, income, education) with smaller effects. These results suggest that public health policymakers must consider how population demographics could affect the deployment of future pandemic mitigation apps. Additionally, other public health efforts, such as general education on vaccination and publicity for public health technologies, may boost the overall acceptance of future pandemic mitigation apps.Implications for Future Public Health Mobile Apps

By articulating the contextual acceptance of various COVID mitigation apps deployed in this pandemic, this study yielded rich implications for future public health mobile apps.

Built upon prior studies focusing on one type of COVID mitigation app [3, 9-10, 26-27], this study compared three types of apps (i.e., contact tracing, test result reporting, and proof of vaccination) that have long-term utility in future public health crises. Our results suggested that people were least comfortable with apps that perform phone-based contact tracing, contrasting the relatively high acceptance and adoption of contact tracing apps early in the pandemic [3]. One explanation is that, as more effective mitigation tools (such as vaccination) become widely available in the US near the end of the pandemic, people may not perceive phone-based contact tracing as necessary or appropriate, especially given its data privacy implications. This highlights the need for policymakers to strategize what public health mobile apps to promote according to the changing pandemic stages and available mitigation methods.

Our findings also shed light on the nuanced implications of the data retention practices of COVID mitigation apps. This study provided initial evidence that people's acceptance of data retention diverged from their acceptance of initial data sharing in specific scenarios, where many respondents felt data should not be retained indefinitely even for the most accepted recipients (e.g., healthcare providers). As we are phasing out the COVID mitigation apps, it is critical to re-evaluate how these apps retain data collected during the pandemic to minimize downstream privacy harms, such as breaches of retained data.

Last but not least, our findings informed how to appropriately deploy future public health mobile apps in the face of emergencies and crises. The different acceptance levels across our vignette scenarios suggest the importance of considering people's contextual acceptance of public health apps' data practices. Deployment of public health apps should start with necessary scenarios that the general public finds acceptable and avoid controversial scenarios. Conclusion

This study systematically applies the CI framework to examine people's contextual data privacy attitudes towards multiple types of COVID mitigation apps that emerged during the COVID pandemic. It confirmed that CI parameters can help predict people's acceptance of using these apps in various realistic scenarios, yielded novel evidence on the acceptance of data retention practices by these apps, and generated rich implications for deploying future public health mobile apps.

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Conflicts of Interest

No conflicts of interest.

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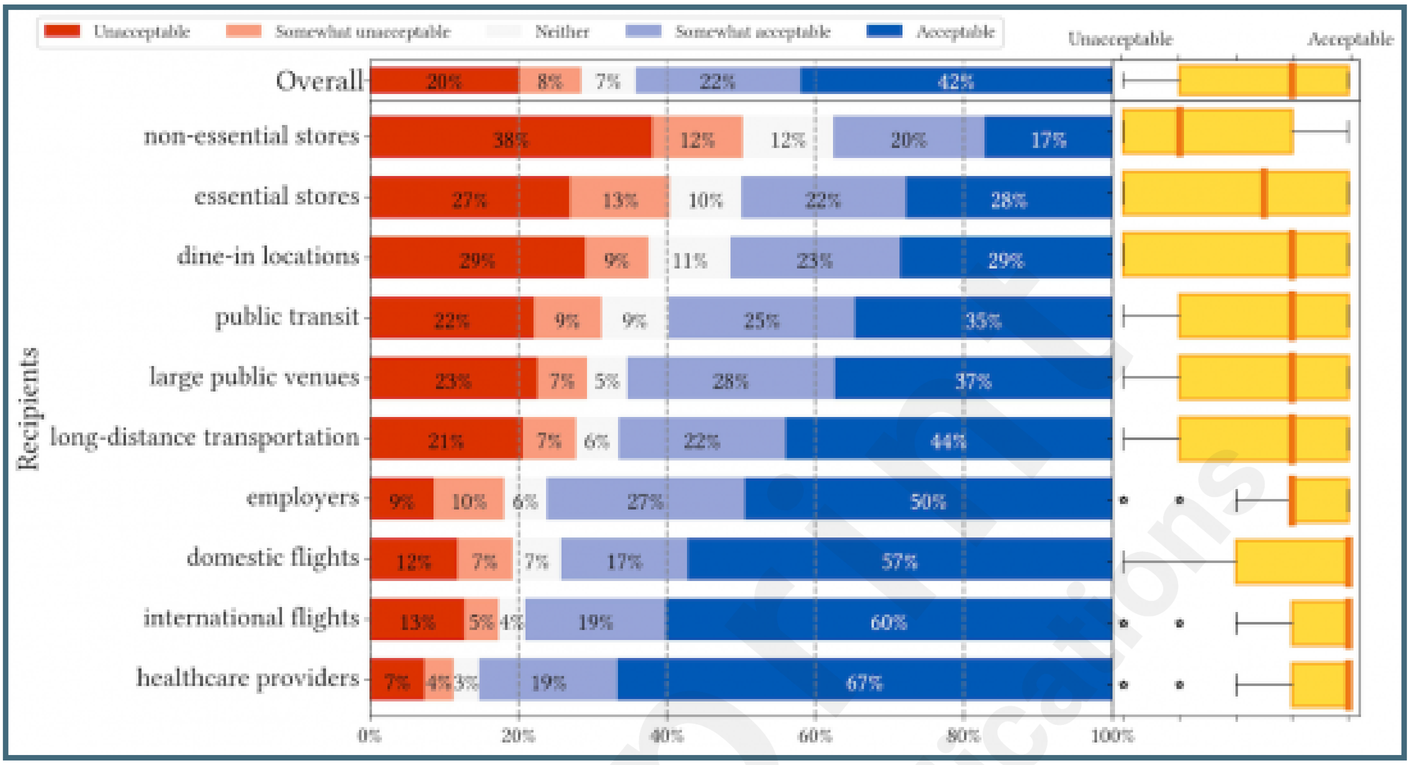
Abbreviations

App: Application
COVID/COVID-19: a disease caused by a virus named SARS-CoV-2 and was discovered in December 2019 in Wuhan, China. It is very contagious and has quickly spread around the world.
CI: Contextual Integrity
95%CI: 95% Confidence Intervals
OR: Odds Ratio
TP: Transmission Principles

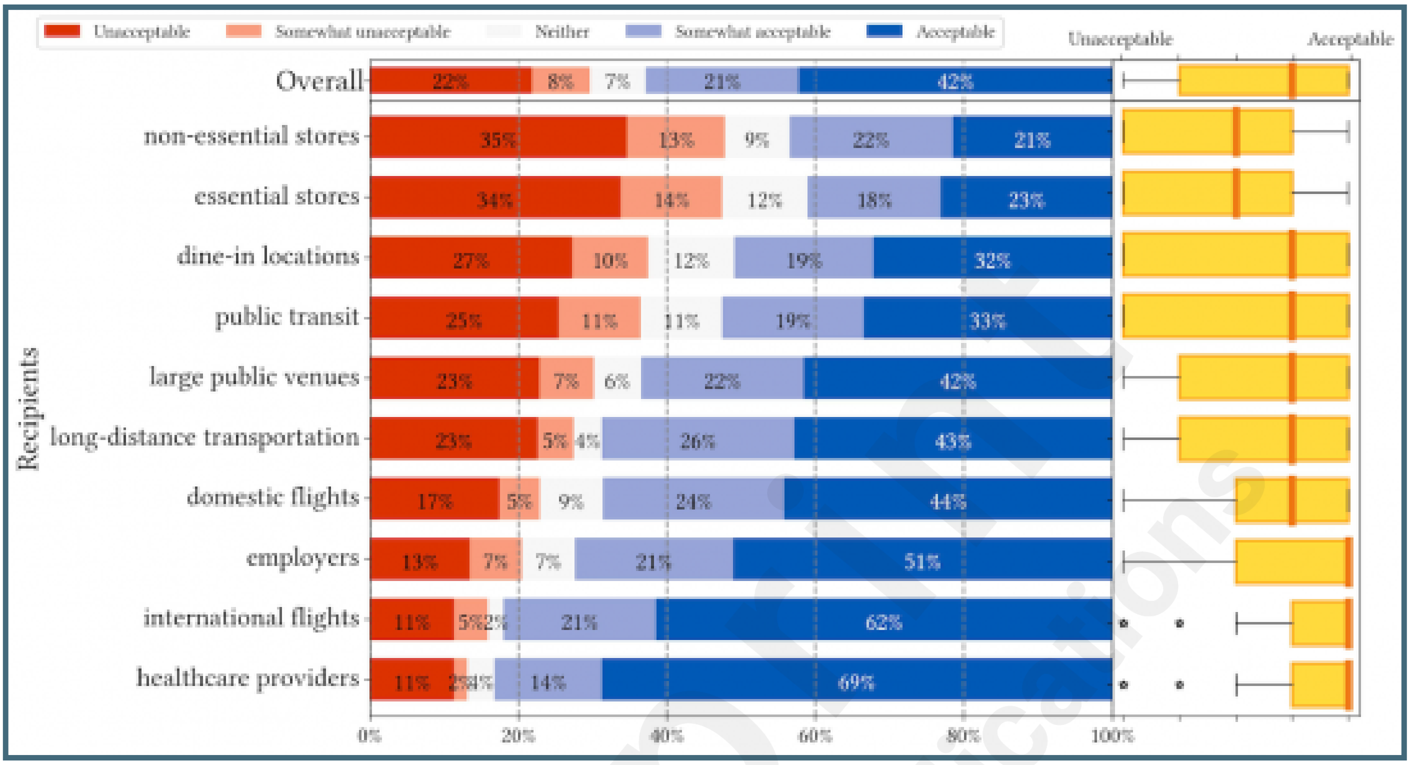
Supplementary Files

Figures

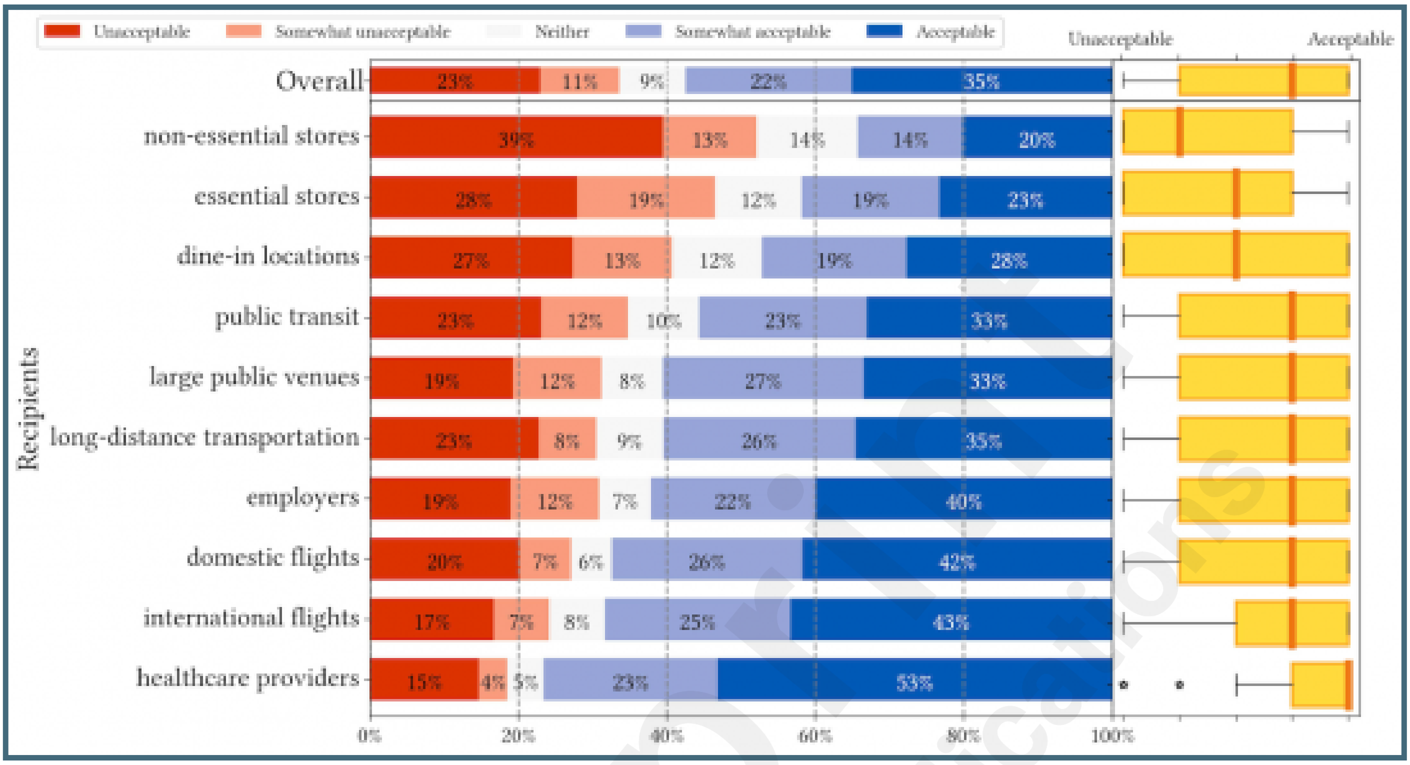
Descriptive statistics of Q1 responses: Acceptance of sharing recent COVID test results in different vignette scenarios, organized by recipients.



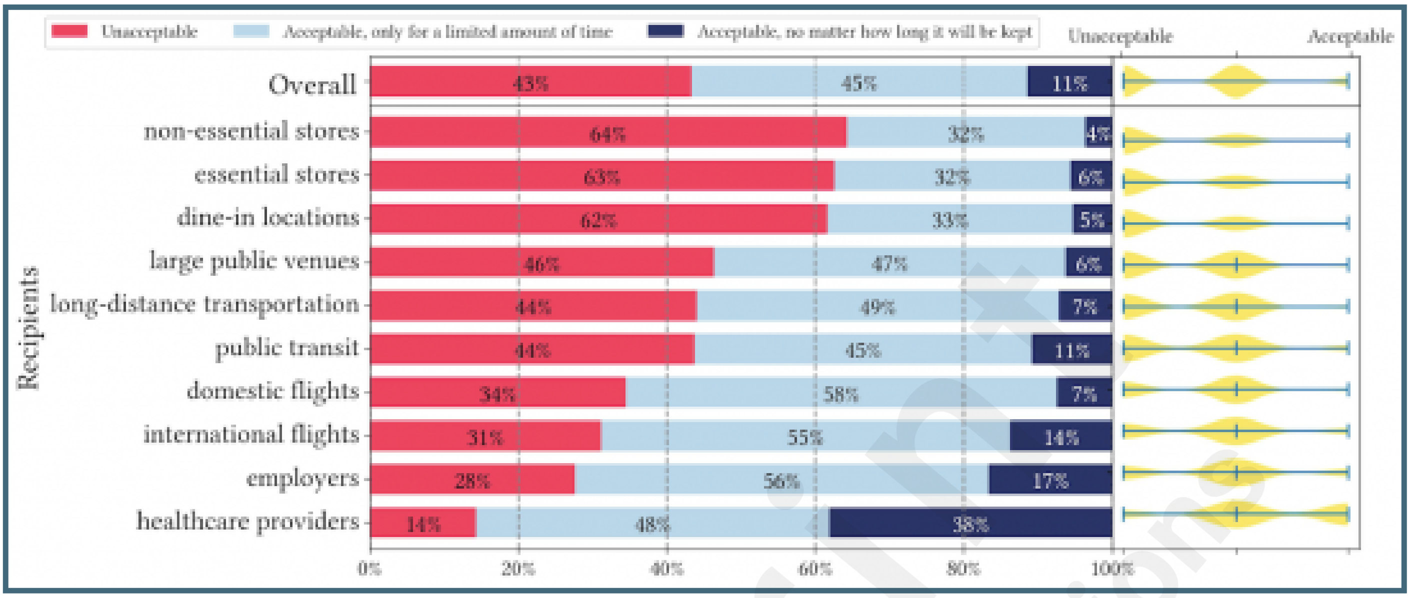
Descriptive statistics of Q1 responses: Acceptance of sharing up-to-date COVID vaccination records in different vignette scenarios, organized by recipients.



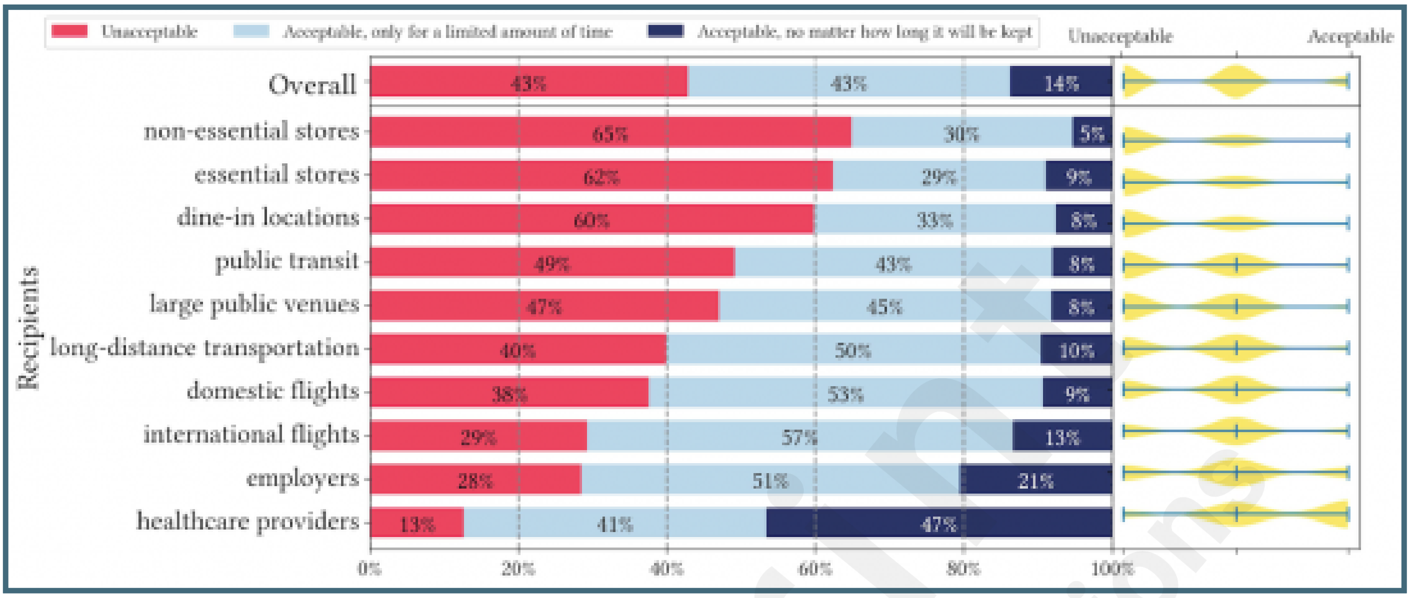
Descriptive statistics of Q1 responses: Acceptance of sharing COVID exposure status from phone-based contact tracing in different vignette scenarios, organized by recipients.



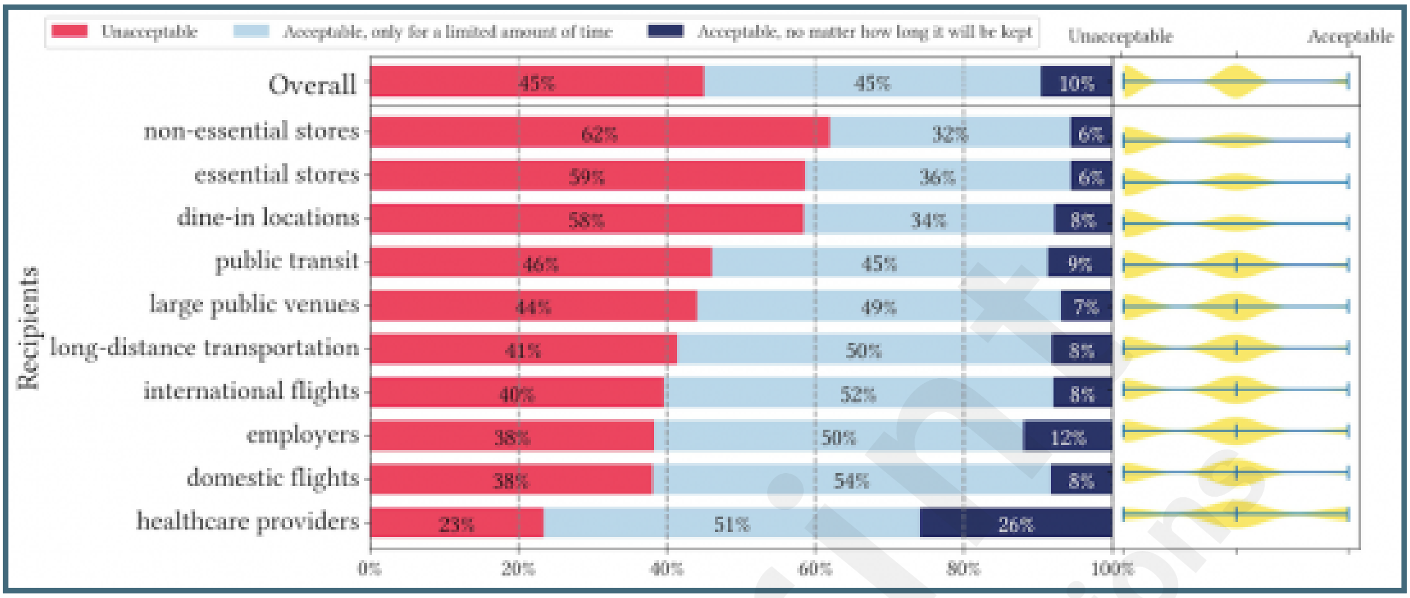
Descriptive statistics of Q2 responses: Acceptance of recent COVID test results being retained in different vignette scenarios, organized by recipients.



Descriptive statistics of Q2 responses: Acceptance of up-to-date COVID vaccination records being retained in different vignette scenarios, organized by recipients.



Descriptive statistics of Q2 responses: Acceptance of COVID contact tracing exposure status being retained in different vignette scenarios, organized by recipients.



Multimedia Appendixes

Demographic distributions of the survey sample.
URL: http://asset.jmir.pub/assets/792eb95363a92c5cd9a8f19c68d0b372.docx