Comprehension from Chaos: What Users Understand and Expect from Private Computation

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**Abstract**

Private computation, which includes techniques like multi-party computation and private query execution, holds great promise for enabling organizations to analyze data they and their partners hold while maintaining data subjects’ privacy. Despite recent interest in communicating about differential privacy, end users’ perspectives on private computation have not previously been studied. To fill this gap, we conducted 22 semi-structured interviews investigating users’ understanding of, and expectations for, private computation over data about them. Interviews centered on four concrete data-analysis scenarios (e.g., ad conversion analysis), each with a variant that did not use private computation and one that did (private set intersection, multiparty computation, and privacy preserving query procedures). While participants struggled with abstract definitions of private computation, they found the concrete scenarios enlightening and plausible even though we did not explain the complex cryptographic underpinnings. Private computation increased participants’ acceptance of data sharing, but not unconditionally; the purpose of data sharing and analysis was the primary driver of their attitudes. Through co-design activities, participants emphasized the importance of detailing the purpose of a computation and clarifying that inputs to private computation are not shared across organizations when describing private computation to end users.

1 Introduction

As data access and collection have grown, so have companies’ attempts to leverage that data, with regulations trailing far behind. Collaborations between companies increasingly involve data sharing and disclosure. For example, Mastercard sold transaction data to Google to track whether Google ran digital ads that led to a sale at a physical store (i.e., evaluating ad conversion) [5], raising privacy concerns for data subjects.

Within such modern data sharing practices, a *data subject* is an entity whose data is present in the data set, while a *data controller* is an entity holding a dataset they are contributing to some analysis. Data controllers who are not themselves the data subject may have different privacy expectations or requirements compared to when the data subject themselves directly contributes their data. The data subject may not have understood their data could be shared or sold [19, 37, 53, 69].

Private computation, encompassing complex cryptographic techniques like private set intersection (PSI) [9, 50] and multiparty computation (MPC) [25, 72], allows companies to analyze and perform computations over data while maintaining data subjects’ privacy in many cases. The cryptography literature emphasizes the value of private computation for cases where the data is especially sensitive (e.g., health or financial data) [66], among mutually suspicious entities [8, 15], or when there are less open trust boundaries [67].

For example, at its essence, PSI refers to a computation where two or more parties each hold a private data set, but wish to collectively compute the intersections of their sets. The intersection can then be shared with one or more of the participating parties. For example, two companies could determine which users they have in common without disclosing the identities of the users not in common. PSI, as with many other private computations, can be implemented using homomorphic encryption, differential privacy, or combinations of techniques that produce different guarantees and efficiencies. Specific privacy guarantees follow from specific mechanisms used in the implementation, such as whether guarantees are based on statistical assumptions or computational hardness.

While private computation is often substantially more computationally expensive and complex than its non-private analogue, there is an assumption that it is in some way better. For instance, it is presumed to be better for privacy that when PSI is used, data is only shared about clients the organizations have in common. To date, the degree to which users perceive private computation as better, or even feasible and plausible, has remained an open question. Similarly, despite a flurry of recent work investigating users’ expectations of differential privacy [7, 35, 36, 71] and attempting to improve communication about differential privacy [12, 16, 21, 32, 43], users’ attitudes about, and expectations for, the broader range
of techniques subsumed under private computation has also remained open. The only user-centered work on private computation [3, 63] has investigated usability from an expert’s, rather than an end user’s, perspective.

To recap, when an organization considers deploying private computation, two key attributes must be addressed: (1) what privacy guarantees can actually be made to data subjects and (2) are those guarantees meaningful to the data subjects whose privacy they aim to protect? In this work, we investigate the second question through 22 semi-structured interviews.

Without knowing what data subjects understand and expect from private computation, one cannot develop tools that empower them to make informed choices. Thus, in this paper we ask and answer the following research questions (RQs):

• **RQ 1**: What do data subjects understand about private computation, and can specific examples facilitate their understanding of the concept? See Sections 5.4–5.5.

• **RQ 2**: Are data subjects more willing to share their data when informed of private computation’s properties (protections and guarantees)? See Sections 5.6–5.8.

• **RQ 3**: How do data subjects perceive private computation’s risks (e.g., inference attacks)? See Section 5.9.

• **RQ 4**: How are perceptions of companies influenced by the use of private computation? See Section 5.10.

2 Background on Private Computation

Private computation is the suite of techniques whose understanding by a broad range of users is this paper’s focus. To provide context for user-centered communications, including highlighting the types of guarantees private computation provides, this section provides technical background information. Notions of private computation revolve around two key aspects: what is being protected, and from whom. Technical privacy guarantees a set of protections given a series of assumptions are met. The assumptions can be about potential adversaries, system complexities, or statistics. When these guarantees are not in place, private information may leak.

A private computation executes a function over an input to produce an output such that there are limitations as to what can and cannot be inferred by an adversary, even if the adversary possesses some form of additional data. The function enforces the limitations through the use of mathematical protection mechanisms from cryptography (e.g., homomorphic encryption) or statistical guarantees (e.g., differential privacy), or some combination of techniques. Such computations may be between two or more parties, and they may involve trusted third parties. What is being protected within private computation typically falls under one of the following two classes:

Class 1: Private Data Set, Public Results. Consider a scenario where one or more parties have a (joint) data set and want to release an analysis of the data set. For example, the Census Bureau may wish to release statistics about the population of a certain region. Abstractly, their analysis \( y \) is a function \( f \) of the data set \( D \), i.e., \( y = f(D) \). The party performing the analysis can employ a protection measure like differential privacy (DP) [18], which ensures that a single record in the data set \( D \) has bounded impact on the analysis \( y \). That is, the output distribution of \( y \) shifts by at most a factor determined by a privacy parameter specified by the analyst. By bounding the impact of a single record, the individual records in the dataset have a measure of protection against being revealed to those who access the results of the analysis. Thus, the analysis becomes a private version of the computation with protections that bound privacy risk.

In some scenarios, the data set \( D \) may be distributed among several parties (e.g., \( D_1, D_2 \)). For example, a government may be interested in the wages of its student population and thus wish to intersect tax filings with various universities’ registration records. Here, the analysis \( y \) may be computed as a secure (multi-party) computation (MPC) [25, 72], which is a cryptographic protocol enabling the parties to compute the function \( y = f(D_1, D_2, \ldots) \) while ensuring that no party \( i \) learns anything except \( y \) and \( D_i \). While differential privacy was the protection mechanism in the aforementioned computation, computations may use both mechanisms. That is, differential privacy and secure computation are composable.

Class 2: Private Data Set, Public Subset. While the previous computations protected all individual data records while revealing the output of a computation, we now discuss a class of protection style that instead aims to publicly (or selectively) reveal a subset of the data. Consider a case where parties want to learn additional information about their data or information about a relationship between datasets they each hold individually. For example, assume Google holds a set of ad views on the Internet and Mastercard holds a set of credit card transactions [5]. Google may want to learn which ad views led to credit card transactions, while Mastercard may want to learn which transactions were preceded by an online ad. Abstractly, given a common identifier in the data, the two parties could learn the intersection of their sets. The process of learning this intersection while protecting their respective datasets is known as private set intersection (PSI) [23]. Two or more parties can compute the intersection of their data without revealing data they possess outside of the intersection using private set intersection (PSI). In particular, PSI reveals no information about identifiers not in the other party’s set, but fully reveals each identifier in common (which may be assumed to already be known). Differential privacy can be used on the datasets for additional privacy [26], and extended forms of PSI can compute a function over the intersection [50].

Attacks on Private Computation. So far, we have defined what private computation protects. However, given that some
information is revealed intentionally as part of a private computation, there are some risks. Recall that we reveal an analysis \( y \) as a function of a data set \( D: y = f(D) \). Given \( y \), it is possible for an adversary to compute the inverse of function \( f \) and obtain a set of possible data set(s) \( D \). This inverse can be computed when given only \( y \), but the adversary may also have background knowledge in the form of a probability distribution over the possible data sets \( D \), further restricting possible inputs and thus improving the adversary’s accuracy.

Inference attacks, a subject of ongoing research, may pose significant privacy risks for subjects in the data set \( D \). For statistical datasets, the risk of de-anonymization attacks or other information leakage can come via the execution of summation queries [39]. In the case of machine learning, attacks may use queries to the model and other attributes. We give a few examples from machine learning where the output \( y \) (given to the adversary) is a publicly released machine learning model (e.g., a neural network), the outputs during a distributed learning process (e.g., federated learning [42]), or both. A model inversion attack [22,27] computes the most likely input for one class of the model. For example, for a face recognition model this can be a picture of the recognized person. A property inference attack [24] computes a property of the records in the data set given a description of the property. For example, for a face recognition model this can be the ethnicity of the recognized person. A membership inference attack [61,73] computes whether or not a given candidate was part of the data set \( D \). For example, for a medical classification model this can be whether or not a patient’s record was included in the study.

Inference attacks are still feasible if the adversary cannot enumerate all possible data sets \( D \), since they only need to estimate the most likely inference. Differentially private protection mechanisms complicate inference attacks [73], but their theoretical analysis is complicated and error-prone [29].

3 Related Work

Communicating Differential Privacy and MPC. While some past work has investigated expectations and understanding of multi-party computation, it has been limited to stakeholders other than the data subjects. For example, Qin et al. focus on the usability of multi-party computation from the perspective of developers [52]. Similarly, Agrawal et al. investigated the perspectives of specialists such as industry professionals, researchers, designers, and policy makers [3]. They found that these specialist participants described private computation as a tool for enabling organizations to work with data. While these specialists acknowledged the importance of end users (data subjects), few prioritized end users’ understanding of private computation, increasing the risk that private computation could be used for privacy theater [63].

The technical privacy mechanism that is differential privacy, and its implications for end users, has received a lot of attention from the HCI research community. Efforts have been made to explain differential privacy using a variety of techniques [12,16,21,32,43] and to evaluate whether differential privacy improves users’ willingness to share their data [7,35,36,71]. Within those efforts there are attempts to convey risk using visuals, risk notifications, and metaphors. In part, the complexity of some of these illustrations can be attributed to the “oddness” of differential privacy. Differential privacy provides guarantees in the form of “two neighboring datasets are indistinguishable within some probability”, and understanding that guarantee requires first understanding the notion of neighboring datasets. However, while past work has done an excellent job at investigating differential privacy, it is too narrow to encompass the implications that correspond to the use of private computation. Private computation, as described in Section 2, encompasses all such computational efforts by organizations where there are protected inputs and revealed outputs, using some protection mechanism, such as, but not necessarily, differential privacy. Therefore, over the course of an interview, we employ what is essentially the process of self-explanation for learning [10]. Self-explanation helps learners adjust their understanding of a topic through examples and explaining concepts back to others. Essentially, it is an inductive, generative process of learning private computation rather than a prescriptive learning process.

Perceptions and Preferences. Previous work has frequently found users to be averse to their data being used by organizations [20,31,40,41,53,60]. As we mentioned earlier, a motivator for the use of private computation is the assumption that it will counteract this aversion. Therefore, it is necessary to study users’ awareness, understanding, and motivations of both technical tools and their implications for individual and societal privacy [4,16,46,55,65]. Information about individuals may be collected by employers, government entities, and friends. Which of these collectors originally receives the information is one component of the ‘context’ or social domain in which information is shared. Recent work from Kacsmar et al. [30] found that when considering different contexts, represented by the number and type of participating companies, there is an observable influence on users’ perceptions of the data sharing practices. Once the information is in a different context, whether via use or disclosure, it can no longer be assumed to meet privacy expectations [44]. In private computation, there is necessarily two or more organizations contributing their data. That is, private computation inherently results in a change of context that can influence participants perceptions and preferences.

Law and Policy. Legal notions of privacy are primarily framed in terms of individual protections from government and from corporations; with legal and financial penalties for non-compliance. The legal guarantees a company makes are typically encompassed within complex privacy policies.
These guarantees are enforced, as much as they are, by local data privacy laws. For example, Canada has PIPEDA, the Personal Information Protection and Electronic Documents Act [48], the United States has the Children’s Online Privacy Protection Rule (COPPA) [68], the Health Insurance Portability and Accountability Act (HIPAA) [2] and the recent California Consumer Privacy Act (CCPA) [64], and members of the European Union have the General Data Protection Regulation (GDPR) [69].

Designers of private computation protocols have suggested that it can help “simplify the legal issues of information sharing” [51] and resolve privacy issues in various domains [14, 34, 49]. However, changing laws takes time while new technologies are in constant development, and thus these laws do not encompass current and future privacy requirements and expectations of private computation [38, 47]. Such legal regulations may impact individuals’ perceptions of privacy and thus necessitate recruiting participants from the same local as one another.

4 Methods

Because there has not been much prior work on users’ understanding of, and expectations for, the broad range of private computation methods we study, we employ semi-structured interviews to allow us to follow up on participants’ responses and allow participants to ask for clarification. All participants received the same set of questions with the order shuffled as appropriate. Appendix B contains the interview guide. We refined our procedure through pilot studies with five participants. Questions that participants found confusing were either removed or clarified. We do not include responses from the pilot study in our results. Our study received ethics approval from the lead institution’s office of research ethics.

4.1 Procedure

Before starting an interview, we reminded participants that participation was voluntary, that audio was being recorded, and that they were encouraged to ask questions throughout the interview. The interview proceeded through the seven parts detailed in the rest of this section: expectations, term awareness, private computation definition and example, computation scenario perceptions, inference attack perceptions, general perceptions, and a co-design activity.

Expectations and Term Awareness. The interview began with baseline questions to establish participants’ familiarity with private computation. For example, participants were asked to “list some of the ways that you expect companies use data about you and others” and whether they had ever “come across” eight terms related to private computation that we presented in randomized order: “private computation,” “encryption,” “hashing,” “multi-party computation,” “differential privacy,” “federated learning,” “private machine learning,” and “secure computation.” Terms with which participants were familiar resulted in follow-up questions about where they had come across the term, what they thought its purpose was for companies and individuals, and a request to define the term in their own words.

Private Computation Definition. We then clarified “private computation” for participants by defining and comparing a non-private computation with a private computation. After participants had the opportunity to ask questions about these definitions, they were asked to consider what they thought could be an example of “a computation where the result could be made public, but the inputs used to determine that result were sensitive and needed to stay private.”

Computation Scenarios. As one of the key parts of our investigation, we gathered participants’ perceptions of, and expectations for, private computation through discussing four scenarios in randomized order. Each scenario consisted of an overall description of the goal of the computation, as well as two ways this goal could be achieved. One way used a straightforward approach involving non-private computation, while the other way employed private computation.

For each scenario, we asked participants how acceptable they found each way of achieving the goal, as well as why. Their explanations and reasoning helped us identify what factors most influence perceptions of (non-)private computation. We also asked participants what differences they perceived between the straightforward computation and private computation in that scenario, how feasible they considered the private computation to be, and how the company performing data analysis might explain the private computation to users.

We select four scenarios to correspond to real-world applications that are permissible under some conditions. Specifically, the four scenarios involved wage equity [11], ad conversion [5], contact discovery [17], and census data [1]. The wage equity scenario described an organization collecting salary data with the goal of generating a report on inequities. The ad conversion scenario described a credit card company and an online company comparing their data with the goal of determining if digital ads lead to sales in physical stores. The contact discovery scenario described a social media company with the goal of determining whether a new user had contacts that already use the app. Finally, the census scenario described a government body collecting a range of data with the goal of informing policies and resource management, as well as making results public. The interview guide in Appendix B contains the full description of each scenario. These scenarios represent three different private computation settings. Ad conversion and contact discovery are settings where PSI can be deployed, wage equity efforts can use MPC, and census data can use privacy preserving query procedures.
We recruited participants based in the USA via the Prolific crowdsourcing service using a survey that included demographic information and when they could be available for a synchronous hour-long interview over a video call. Participants received $1.45 USD via Prolific for the initial scheduling survey (average time 4 minutes) and an additional $30 USD for participating in the interview. While most interviews lasted between 50 and 60 minutes, the shortest was 40 minutes and the longest 90 minutes. These times include debugging technical issues (e.g., a participant fixing their microphone).

Inference Attack Perceptions. We then presented participants with four descriptions corresponding to a type of inference attack. For each, we gave participants a series of examples of what specifically the company could learn, asking the participant to explain how acceptable they found that situation. For instance, in the case of a membership inference attack, we said, “One of the participating companies will additionally be able to learn which specific records in the computed result correspond to you.” The membership inference case examples included the dataset being a set of dating app members, a set of frequent drug users, a set of low-income households, and a set of people with a specific health condition. For each example, participants were asked how acceptable it is if the organizations involved could determine they were a member of the example dataset, as well as to explain their reasoning. The other attacks corresponded to model inversion attacks, statistical inference attacks, and property inference attacks.

General Perceptions. At this point, participants had engaged with four private computation scenarios, as well as four types of inference attacks. To unite these ideas, we asked how the participants thought companies should be communicating to their customers about how they used their data (with and without private computation) and what they felt were the companies’ responsibilities to their customers.

Co-Design Activity. We concluded the interview with a codesign activity that built upon all topics participants engaged with throughout the study [62]. We asked participants to pretend they were working at an organization that hoped to use private computation and then consider how they would choose to explain private computation to their customers or clients. Participants were able to write, draw, verbally respond, or use whatever other means of communication they preferred. After providing their own explanation, participants were shown all previous participants’ responses to the question and asked what they would add from their own to that explanation and what (if anything) they would remove from it until they arrived at their final version of the explanation.

4.2 Participant Recruitment

We recruited participants based in the USA via the Prolific crowdsourcing service using a survey that included demographic information and when they could be available for a synchronous hour-long interview over a video call. Participants received $1.45 USD via Prolific for the initial scheduling survey (average time 4 minutes) and an additional $30 USD for participating in the interview. While most interviews lasted between 50 and 60 minutes, the shortest was 40 minutes and the longest 90 minutes. These times include debugging technical issues (e.g., a participant fixing their microphone).

4.3 Data Analysis

We recorded audio from each interview. We automatically transcribed the audio via speech-to-text software; afterwards, a member of the research team listened to each recording and corrected the automated transcriptions, as well as grouping responses by question and section of the interview. We analyzed this qualitative data using an inductive approach, allowing themes to emerge. Two members of the research team extracted participant responses and then collaboratively clustered them according to similar sentiments and themes using the affinity mapping procedure [28, 33, 59]. Affinity mapping allows us to employ a team-based, collaborative approach to iteratively identify all aspects participants articulated when discussing their understanding of private computation, as well as private computation’s implications. As part of the iterative affinity mapping process, after the two researchers formed initial clusters of participant quotes, they reviewed each quote within a theme to see what they had in common and discuss whether the quotes contained any points not encapsulated by others within that theme. Through iteration, we ensured that unique insights were not overshadowed by more prevalent ones. This process enabled us to capture the full range of attributes participants considered, as well as those that most commonly influenced their opinions.

4.4 Limitations

While we strived to ensure a diverse sample in many aspects, our participants represent a convenience sample and skew young (less than 20% of participants were age 45+) and educated (69% had completed a bachelor’s or graduate degree). Our participants are WEIRD (western, educated, industrialized, rich, and democratic), and we make no claims as to our results being representative of other population groups [58]. All of our scenarios are based upon typical cases in North America, where our participants live, and some examples may not be permitted by laws in other countries. Similarly, our scenarios may not cover data analysis tasks that might be both legal and common outside North America. Finally, as with other response-based studies, we acknowledge the potential for bias with respect to what participants perceive as socially desirable behaviour [54].

5 Results

From analysing participants responses, we evaluate the development of participants understanding of private computation from their first descriptions through to the final explanation they construct at the end of the interview. We identify themes participants use in their decision-making process when considering our data sharing scenarios. We describe how private computation descriptions influence participants perceptions
Table 1: Participants’ demographics, including age range, gender, and highest education completed. Participants indicated whether they have an education or work experience in a tech-related field, as well as in cryptography in particular.

| ID | Age      | Gender | Education       | Tech | Crypto |
|----|----------|--------|-----------------|------|--------|
| 1  | 18-24    | Woman  | High School     |      |        |
| 2  | 18-24    | Woman  | Bachelors       |      |        |
| 3  | 35-44    | Woman  | High School     |      |        |
| 4  | 45-54    | Man    | Bachelors       |      |        |
| 5  | 25-34    | Man    | Grad School     | ✔    |        |
| 6  | 55-64    | Woman  | Grad School     |      |        |
| 7  | 18-24    | Man    | Some college    | ✔    |        |
| 8  | 25-34    | Man    | Bachelors       |      | ✔      |
| 9  | 25-34    | Man    | Bachelors       |      | ✔      |
| 10 | 25-34    | Man    | Grad School     | ✔    | ✔      |
| 11 | 45-54    | Man    | High School     |      |        |
| 12 | 18-24    | Man    | Some college    |      |        |
| 13 | 35-44    | Woman  | Bachelors       |      |        |
| 14 | 25-34    | Man    | Some college    | ✔    |        |
| 15 | 35-44    | Man    | Some college    |      |        |
| 16 | 35-44    | Man    | Bachelors       |      |        |
| 17 | 25-34    | Man    | Bachelors       | ✔    |        |
| 18 | 35-44    | Man    | Grad School     |      |        |
| 19 | 35-44    | Woman  | Some college    |      |        |
| 20 | 55-64    | Woman  | Grad School     |      |        |
| 21 | 25-34    | Woman  | Some college    | ✔    |        |
| 22 | 25-34    | Woman  | Bachelors       |      |        |

of the scenarios and report their expectations in terms of companies’ responsibilities when using their data.

5.1 Participants

As detailed in Table 1, we interviewed 22 participants falling in the following age ranges: 18-24 (4 participants), 25-34 (8), 35-44 (6), 45-54 (2), and 55-64 (2). Among participants, 10 identified as a woman and 12 as a man, with no other gender identities being used. The participants fields of work span a broad range including politics, librarians, environmentalists, educators, insurance, health, music engineering, technology, personal assistants, chiropractics, and marketing. In terms of the highest level of education completed by the participants, the distribution is as follows: five participants had completed a graduate degree (Masters or PhD), eight completed a bachelors or associates degree, six completed some college but no degree, and three participants completed high school. Further, six participants reported that they “had an education in, or work in, the field of computer science, computer engineering, or IT” and of those one reported that they “had an education in, or work in, the field of cryptography.”

5.2 Initial Expectations of Data Usage

Participants initial expectations for data usage could influence their perceptions of private computation. Thus, we started by asking participants what their expectations were. Participants had expectations in terms of what data companies use (purchase history, demographics, search history, salary data, and user preferences), what companies use the data for (financial gain, improving services, forging social connections, and personalization), and companies’ responsibilities with respect to the data (anonymization, preventing re-identification). P8 emphasizes that despite being aware of companies’ practices, they do not necessarily approve or agree with how companies use their data:

“Even though I don’t love that, I expect them to use it like for their marketing purposes [...] grow the bottom line of their business, to make money off of my data, and who I am as a person.” (P8)

Participants have an expectation that companies are protecting the data entrusted to them, but P18 expressed concern that data usage practices may go beyond what they expect and be for reasons which they are not even aware of.

5.3 Initial Awareness of Terms

As a proxy for identifying any preconceived notions participants may have about private computation, we showed participants a set of terms from the space (see Section 4.1). All participants expressed familiarity with the term encryption, with a few also being familiar with the term hashing. Familiarity with hashing was limited to those with a technical background who came across it as a data mapping strategy. All other terms either had no participants reporting familiarity or participants could not place the origins of the familiarity. In these cases, the participants guessed they either came across the phrase in terms and conditions or in news articles.

Source of Awareness. We surmise that the term encryption is thoroughly embedded in various facets of day-to-day life. Participants responded that they learned of encryption via leisure, education, employment, and when managing finances. However, encryption is not viewed as being particularly relevant to participants lives:

“[It’s] something that’s used by techie people or politicians or people who are doing nefarious things, I don’t think of encryption as guaranteeing things for individuals, like the lay public like myself.” (P6)

Guarantees. On one side, participants expressed skepticism as to what tangible protections encryption can provide. Emphasis was made that there are “no guarantees” (P16) and that while it may provide some protections encryption does not make it impossible for malicious actors to access things. For those that are more optimistic of the protections encryption provides, it was viewed as a means of making it more difficult for unauthorized persons to access the data.
Companies’ Purpose. Some participants responded that encryption is used to provide the “illusion of security” (P8) while others thought encryption is used to provide “customers safety with their data” (P21). Ultimately, whether they had confidence in the protections or not, participants reported that company’s use encryption to their own benefit; whether it is for protecting customer data, protecting proprietary information, gaining customers trust, or avoiding legal penalties.

Defining Encryption. In general, participants’ definitions of encryption were not fully comprehensive, but they did show an understanding of encryption at a conceptual level. Essentially, participants highlighted that encryption changes the information it is applied to. These changes were referred to as “scrambling” (P20) and “masking or disguising” (P15) the information. Further, the changes are done with the goal of providing some security to the information such that it cannot be read by unintended recipients. These responses, regarding transformations, are most inline with what past work termed an Iterative mental model of encryption [70].

5.4 Defining Private Computation

We asked participants to produce a definition for private computation at three points throughout the interview. We observe an increase in understanding via participants own explanations of private computation from the start of the interview through to the end.

First Attempts. They were first asked to provide their own description of private computation after they were shown a definition and asked to think of an example that could fit the definition. This definition occurred before participants were shown any of the scenarios included in the study. Participants struggled to provide an initial definition of private computation. Some participants were unable to come up with a definition. Of those that did provide a definition, they were generally brief, and typically overlapped with the initial definition they had been shown.

Participants did come up with several examples in response to the prompt for “an example of a computation where the result can be made public, but the numbers used to determine the result are sensitive and need to stay private”. Not all participants came up with an example, some came up with more than one, and some participants changed their mind about their example fitting the prompt (see Table 2 in Appendix A for the list of examples). The subject domains of the examples included salaries, research studies, and organizations profit data. The public outputs included aggregates, averages, company trends, and post-processed data. While not all of the examples were appropriate settings for private computation, the participants identified a number of cases that already exist. In particular, participants identified examples that corresponded to two of the scenarios we used later in the study; census data and wage equity.

Second Attempts. At the end of the study, the participants were asked a second time to explain private computation. At this point, they had seen all four private computation scenarios and the cases corresponding to inferences attacks. For the second explanation they were informed that they could use any medium, including drawing a picture, verbal explanations, and writing. Participants’ second attempt at providing an explanation for private computation was overwhelmingly more successful than their first. Every participant provided a definition with their chosen medium varying (see Figure 1 for a selection of responses). Each definition was reasonably accurate, even if it was not all encompassing. Participants included in their descriptions what is being learned and what is being protected as important. Other aspects they suggested to include were how it will benefit the client and what the computation actually is. Further, in addition to their explanation, participants also identified attributes that they considered critical to quality explanations. Attributes participants emphasized are transparency and honesty. Participants also recommended including examples (especially as figures), summaries, and visually placing emphasis on critical points.

Final Explanation. Participants final definition is the one they derived after seeing the previous participants’ final answer. Each participant was shown the explanation derived (by consensus) by the previous participants. They were then asked what they would add or remove to the current explanation with consideration to their own initial response to the prompt. Earlier in the study participants made more dramatic changes, and they often incorporated large portions of their own explanations with smaller components of the current collective explanation. As the interview study progressed, participants made fewer and smaller changes, adding finesse as they identified attributes they considered valuable for an explanation being directed at the public.

When they made changes to the derived explanation, participants expressed the importance of clarity, accuracy, and conciseness. Participants emphasized that the value of being concise, but that it needs to be balanced with accuracy. For example, P17 noted that the original example would actually not protect the inputs:

“The only thing I noticed is like, in this example, it’s obvious the data is too small; that you can tell like the ages of specific men and women just because there’s only two men and two women.” (P17)

While it is the case that if “You add too much and you start losing it” (P16), without sufficient details, customers and clients could be confused or misled. Ultimately, participants made changes to improve clarity across steps in the illustra-
Secure computation is a way that a company analyzes your data. The final analysis will be made public [at access location]. However, your specific data is protected and cannot be traced back to you nor can your specific data points be traced back to you. The analysis will be specifically [example], and this is being done because [purpose].

This is the information we’re getting from you, but, rest assured, only Part Three will be shown. You can trust us to keep your information private. <If true>This information will only be used for this project and nothing else in the future.

Figure 2: Final explanation of private computation derived via input from the series of all interview participants.

As they constructed their explanations, participants did not focus on wanting to know the details of the mechanism used to achieve the guarantees. Participants trusted that the functionality was feasible without the details; leaving no need for complicated metaphors to prove it (Section 5.5). This eases the difficulty of communicating private computation practices in a way that is relevant, actionable, and understandable to the populace [57].

Based on the derived explanation, they did want to know the inputs, the outputs, the guarantees, and most of all the purpose of these computations. The components of the final derived explanation were: a description of the concept, what was being done and why, an illustrated example, and a brief explanation of the implications the computation could have for them. Further, these components are aligned with the themes that emerged when participants explained the acceptability of the four private computation scenarios. This consistency suggests these attributes are critical to members of the population being able to give informed consent to private computation. The remainder of this section revisits each of the components included in the final definition derived by participants; and provides insight into why these components were considered relevant by the participants.

5.5 Feasibility of Private Computation

In terms of feasibility, participants overwhelmingly considered the private computations in each scenario to be possible. Not only did participants think the scenarios were possible, but they thought such computations may already be happen-
Within our sample, participants generally perceived some private computation descriptions used for both the ad conversion and contact discovery as improvements: that companies cannot use the data for any other purposes are simulations restricting the amount of data revealed and ensuring that companies should spend more money on such projects to ensure that they are secure and safe (P2, P20, and P22).

5.6 Initial Perceptions of Scenarios

Within our sample, participants generally perceived some scenario goals more positively than others. Specifically, the scenarios for wage equity and census data were generally positive, with responses clustering on the acceptable end of the scale (with few respondents considering these goals unacceptable). The scenarios for ad conversion and contact discovery, however, were viewed less positively. For both of these, the responses clustered on the unacceptable end of the scale. For instance, after they considered the contact discovery description, P14 responded that:

"...it’s you know, whether there are guards in place, it’s do we have cops to to make sure that they’re going to do what they’re supposed to do." (P16)

Participants acknowledged that performing private computations could be more expensive (which was stated in scenarios where appropriate). When they considered the costs, participants included both the company’s perspective and their personal views. Ultimately, while participants noted that companies may lose revenue by using such computations (P4 and P11), this was not considered to be an excuse to not protect their user’s privacy. Participants even advocated that companies should spend more money on such projects to ensure that they are secure and safe (P2, P20, and P22).

5.7 Potential for Influencing Acceptability

For each scenario, participants view two descriptions, one corresponding to a private computation technique and one not, that could be used to achieve the organizations goals. The private computation descriptions used for both the ad conversion and the contact discovery scenarios see a positive change in acceptability. Wage equity has the most significant improvement with no participants reporting the private computation scenario to be unacceptable.

With respect to the private computation scenarios, the stipulations restricting the amount of data revealed and ensuring that companies cannot use the data for any other purposes are cited as improvements:

"Even less of the data...data that is not relevant at all, they modify it to not make it available and I think that’s, that’s very thoughtful" (P9).

When considering the above attributes participants responded that “it feels a little bit more protected that way” (P12), “aligns a smidge more with my values” (P8), and “sounds like another layer of security” (P19). Overall, the descriptions corresponding to a private computation trend towards improving participants perceptions in terms of acceptability: “they’re not, you know, over exploiting what they’re getting” (P22). The exception to the observed improvements with respect to acceptability is the scenario for census data; which actually has the opposite effect:

“It feels like the second one’s kind of saying the same thing. It just they’re trying to make it sound a little bit better” (P19).

However, even for the more acceptable scenarios the improvement is not unconditional. Participants still express concerns for aspects of privacy that the private computations do not or cannot address. As said by P7, “At the end of the day they’re still like learning specific things about me.” (P7) Ultimately learning something is the goal of any private computation, and that is not something that can be changed.

5.8 Conditions for Improving Acceptability

For each scenario, participants are asked how acceptable the scenario is and how companies should explain the private computation if they use it. Across scenarios, participants express a range of conditions that influence the acceptability.

Motives Matter. When responding to how acceptable they found a scenario to be, one of the conditions participants placed upon their answer was the goals and intentions of the company (P22) and whether the participants considered the reasons to be just and fair (P11). Goals that benefited society tended to shift their responses towards the acceptable end of the scale and goals that corresponded to financial gain tended towards the unacceptable end of the scale. The scenarios for census data and wage equity were viewed as benefiting society. In the case of census data, participants went as far as to say: “it’s like, crucial information gathering” (P8). Factors for participants when they viewed the census description included trust in the government, importance for society, and how such data is used:

“And if the government is going to spend money, it may as well be based on some data rather than shooting from the hip.” (P6)

Similarly, the wage equity description was considered to provide an important societal benefit that prioritized fairness and countered discrimination:

“Wage equity should be a goal of a civilized society and companies aren’t going to do that on their own. So third party organizations come in to try to
wanted to know “who is making the decisions regarding the dependent on the information in question:

phasized that the acceptability of such restrictions is highly

In particular, the ad conversion scenario was seen as exploita-
tive and unnecessary:

Want to determine whether […] their ads are effective? Well, you’re still in business right? See, that for me, that’s enough.” (P16)

Some participants expressed that they understood why the company would want to perform such computations to de-
termin if the money they spend on advertising was effective. Participants that expressed such understanding were still divided in that while some also thought it was fair, others thought companies should determine effectiveness without using additional personal data: “companies should have their own analytics […] to figure out their own conversions” (P21).

Regulate the Restrictions. In the census case, there was actually an increase in the number of participants that consider the scenario to be unacceptable or completely unacceptable. Participants expressed concern both about the aspect of “any query” being permitted as well as about how query restric-
tions would be determined. Participants expressed concern that companies would exploit such restrictions such that “it’s more like withholding information” (P18) and therefore they wanted to know “who is making the decisions regarding the information that’s permitted” (P8).

Essentially, participants views were dependent on who makes the restrictions as well as what they restricted. For instance, P16 spoke about the importance of allowing the public to replicate results themselves whenever possible. They supported protecting individuals, but emphasized the importance of balancing protections with transparency:

“If we’re talking strictly numbers I lean towards all information available. There shouldn’t be any math problem that that is is hidden.” (P16)

This view was shared by other participants who also em-
phasized that the acceptability of such restrictions is highly dependent on the information in question:

“...depending on what information is permitted, it might be good for somebody to know something that they’re not permitting through the system, or it might be bad to let people know something.” (P13)

Finally, some participants considered both descriptions to provide insufficient protections and desired additional restric-
tions (P5 and P10). These participants suggested a hybrid version of the descriptions to produce what they considered to be a more privacy preserving version. Specifically, to address their concerns, they suggested a query variant that only allows aggregate (or average) based queries while also preventing inferences beyond what is permitted.

Divulge the Details. Identifying what information individuals prioritized in their decision making is key to ensuring that information is communicated in the future. Participants mentioned a number of details for inclusion in explanations, and indicated such details are an influence on acceptability. In particular, participants who responded that a scenario was less than acceptable (e.g., neutral or unacceptable), empha-
sized that further information is required before the scenario could be acceptable. First and foremost, participants wanted to know that their data is being used:

“That it’s [the data is] being used. What’s being done with it. The other company that is involved, that is Having access to it, and if it’s going to be like ongoing or not.” (P17)

Beyond knowing their data is being used, participants wanted to know how the data is being used. They wanted to know who is doing the computations and why they are being done. They wanted to know how long the data is being used for, how the data is protected (including the limits of those protec-
tions), and the implications for them if their data is used in these ways. For some participants, a failure to provide details or implement any of the protections the organization claims, are reasons to decline to participate in private computation. In other words, even when private computation is employed, participants care about appropriate flows of information [44]. Participants want to be allowed to judge if a flow is appropri-
ate for themselves, and to do that, they require details with respect to the information flows.

Consent Above All. The details participants expect to be provided with are not just about the information. Rather, par-
ticipants’ desire to be informed is a means to an end. Ulti-
mately, participants expressed a desire to have autonomy over their own data through informed consent:

“Every time your data is used in some kind of computation, you should be specifically alerted by the company; they shouldn’t be able to do private computations […] without you being aware of it.” (P13)

A theme that emerged across all scenarios from the interview is consent and the importance of choice and communication to have meaningful consent. P17 summarized this notion as:
Participants, such as P1 and P16, both emphasized that consent is not a one-time thing. Companies need to be informing individuals periodically, or “every step of the way” (P16), about how their data is being used and ensure that they continue to consent to the use of their data:

“When they sign up for the credit card and periodically, they should be reminded that all of their data is, you know, being sold to other companies.” (P1)

In cases where participants may want to withdraw consent, the means to do so should be clear and accessible. Companies need to be “giving simple directions of, you know, where to go to opt out on the application” (P4). Such directions support individuals who change their mind about data use as well as those who did not understand or intend to agree:

“There is a system where if a person finds out that they sign something that they really didn’t understand, they can have a way to retract their permissions or whatever.” (P13)

The final attribute participants emphasised as critical for consent is the use of clear and transparent communication. That companies need to be “proactive” and “not just rely on legal contracts to protect them”. For instance, when informing individuals about how their data can be used, it should not be buried in terms and conditions nor obfuscated by legalese:

“Be more upfront about how they’re using our data instead of varying it in like really wordy terms and conditions in language that the average person like myself...like we can’t understand it very well.” (P1)

5.9 Risks, Limitations, and their Implications

We now discuss participants responses associated with the perceived risks and implications of private computation. In addition to the specific risks discussed at the end of the study (the inference attacks), participants highlighted what risks they perceived as possibilities in this space.

Risks and Implications. Participants question the potential implications of private computation and identify a number of risks associated with private computation. Our participants expressed concern that they “can’t really figure out [...] the implication” (P6) of the computations or “how it could be exploited” (P15). As expressed by P22, the concern is that companies may request limited information, but try to gain additional information via some other means:

“If you’re only giving like limited information, you might wonder if they’re gonna acquire other personal information about you from that limited information.” (P22)

This concern, that organizations might make inferences from the limited information was brought up by P22 before any of the inference attacks were discussed.

Further, there are risks associated with the contexts in which private computation could be applied. Both P13 and P19 identify risks associated with the goals of the scenarios, regardless of the use of private computation. Individuals can be in situations where computing such connections could put someone’s safety at risk. For instance, after considering the contact discovery scenario, P19 expressed concern that such connections could reveal someone’s internet presence to an abusive ex or someone they have a restraining order on:

“Through [...] common contacts that now he all of a sudden has a friend who has her information and now he has her information if through the tangled web, you could be able to find people [...] that’s a growing problem.” (P19)

Such risks are not things that can be resolved with a technical solution, such as private set intersection, but instead highlight the importance of informing users and gaining their consent, respecting their own risk assessments.

Limitations of Reassurances. While some participants expressed exceptional insight into the risks and implications of private computation, others felt reassurance from its attributes. Unfortunately, not all of the attributes that gave reassurances actually provide the protections that participants expect. We identified two main concepts that participants find reassuring but are known to not provide the guarantees attributed to them. The first concept that provides false assurances is aggregation. For example, P6 described the protection from aggregation as:

“When it’s aggregated. It’s lost. It cannot be disassembled. And private does not communicate that in any way shape, or form to me.” (P6)

This confidence in averages and aggregation is unfortunately misplaced, as we know that there are a number of ways a malicious party could carefully select queries such that they can learn about an individual [39]. The idea that one can “blend into the crowd” via averages and aggregates and not experience additional risks is also observed in participants responses to the assorted inference attacks they were shown. That is, participants tended to find property inference attacks more acceptable than attacks that targeted an individual.

The second concept that provides false assurances is law, policy, and standardization. The assumption that the practices are “legal” or “industry standard” influenced acceptability.
For example, P4 specifically stated that if the practice is not an industry standard then the acceptability would decrease. In the cases of P16, they concluded that if companies disclose such practices in their terms and conditions, it must be legal:

“I don’t know if in the real world, if this is legal to do, I would assume it’s legal if they, if it’s in their terms, right?” (P16)

However, while participants expressed confidence that the law protects against improper data sharing practices, this belief is not universal. Some, such as P11, stated that such practices do “not sound ethical [-] even if it’s legal.”

Inference Attacks. Across all inference attack examples, the perceived sensitivity of the data is a factor for the acceptability. Location data, health data, sexual orientation, and religion are cases where the type of data is deemed to be more sensitive. Of particular concern were the cases that included health data. Participants, who were all located in the United States, expressed concern that their insurance company would get this information:

“If that information then got shared with like my insurance company [they] would then decide to raise my rates because maybe I am at an increased risk for heart disease.” (P1)

Among participants there was concern that the inferences made through the attacks could be used in malicious ways and to propagate bias and discrimination:

“What this data is going to be used for, the state of it, should be used to to propel humanity forward. Not hold, not keep people back.” (P16)

With respect to the inference attacks, some participants viewed all such attacks as unacceptable; since the companies were "not supposed to have that information period” (P6).

However, we did observe that inferences that target groups rather than individuals were less negatively viewed. Inferences about properties of groups are generally perceived to be somewhat more acceptable, however, this trend is conditional upon the specific property and the potential implication that property has for individuals and society. For instance, if the property could be used to “manipulate the populace” (P13), is “rude”, or “discriminating” (P22), then participants state it would be less acceptable.

For conditional attacks, information leaks only occur probabilistically. However, this was not necessarily viewed as an improvement by participants:

“It’s based on what is what that record is, is in relation to even if it needs to be protected and it should be protected 100%.” (P16)

Many found it unacceptable regardless of the percentages and stated that percentage was irrelevant. Of those that found a tipping point to neutral or acceptable they either tipped at 50%, 25%, or 1-2% chance the exact record would be learned.

5.10 Expectations for Reform

An individual’s ability to protect themselves is almost inconsequential without support from both government and the companies using the data. For example, after expounding on how a company’s priority is their organization and financial gain, P6 expressed concern for how they are supposed to learn what they need to have data autonomy:

“...how do I protect myself and who teaches me how to protect myself? Who’s responsible for teaching me how to protect myself?” (P6)

Participants identified responsibilities for companies, government, and even themselves as individuals. Companies have the most responsibilities with respect to the law, protecting user data, and treating data with respect. The governments responsibility is to protect individuals via the creation and enforcement of appropriate regulations.

Re-humanize Data. When working with customer or client data, companies need to remember that the data corresponds to real people. Companies are expected to protect the data entrusted to them using the “best” security measures available to them as that data is not just some abstract input they compute over. Rather all of the data they hold corresponds to an “actual individual person with a name, a face” (P9). The data companies collect has been entrusted to them. Companies are expected to treat the data with respect and to be aware that the data is something important that they are responsible for. Treating data recklessly can have consequences for actual people:

“I think the ultimate responsibility is to use it with caution. To protect people’s privacy. It’s up to the company to make sure they only share to the extent, the person allowed them to.” (P9)

Furthermore, respecting the people who are represented by the data requires companies to exercise clear communication. Without transparency into data sharing practices people will continue to struggle to have autonomy over their data.

Proactive and Transparent Communication. When using customer data companies need to be upfront about their actions, but also provide greater granularity of control. For example, rather than a vague description for individuals to agree or disagree to, companies can be more specific:

“You either agree or disagree and it doesn’t really give much more information on what type of data is being used.” (P12)
In addition to being specific, companies need to acquire explicit and ongoing permission for the collection and use of data. One participant even hypothesized that data sharing practices would be more positively received overall if there was not so much obfuscation and manipulation in the space:

“A big social outcry all over [...] that could really be prevented if they were open from the very beginning. If people just knew, they wouldn’t be so spooked by it.” (P9)

Regulation and Enforcement. While some participants called for clearer regulations, some directly called for the practice of companies selling data to be made illegal:

“They need to stop selling our information in general [...] when you’re talking about passing that information to a company, I just I think it should be illegal.” (P19)

However, in terms of law and regulation, participants tended to agree that companies have the responsibility to follow the law and the government has the responsibility to enforce the law, regardless of the use of private computation:

“Health is a sensitive topic and and they’re already legal protections for health information and so on. So, I don’t see how why this edition of technology should should change those protections.” (P16)

Participants made suggestions as to how the law can be enforced; specifically they suggested employing independent third parties. For instance, P21 suggested a third party could perform compliance checks and P1 suggested an independent entity to review points critical to consent. The independent party would perform a review to determine the best way to communicate to users about how their data is being used. They would also determine what information users need to make an informed choice about their data: such as a set of points everyone using the service should know about.

6 Discussion

Companies as Custodians not Owners. Participants expect the companies that use their data to treat it with respect. To treat the data is something important that has been entrusted to them and not something they have ownership over. While meaningful consent is a challenge to achieve, it goes a long way to fostering trust in an organization and willingness to provide data. Several attributes previously found to be relevant to individuals data privacy decisions are still very relevant within private computation. In particular, participants emphasized the importance of knowing the purpose or goal as well as a requirement that companies gain consent from their users before sharing their data. Even when using private computation, companies must communicate with the same level of transparency, including details related to how the computation is being used and what the company could potentially learn as a result of the computation. Communication should be transparent, accessible and clear and the onus is on the companies to ensure they get informed consent. In short, a lot can be forgiven if permission is given.

Limitations of Technical Privacy. While technical solutions are a powerful tool for protecting data, such protections do not directly correspond to personal privacy protections. The data being protected in these scenarios is not just an abstract concept, but instead is a placeholder for individuals with real lives and all the complexities that entails for their threat models. As a community, security and privacy researchers and developers need to remember that the protections provided by protocols and constructions do not and cannot encompass the full range of risks experienced by individuals in society. Technical privacy solutions must be conscious of the space which they may be deployed in and not guarantee that which cannot be delivered. This does not mean that such solutions do not add value, but that value must not be overstated. We must not forget that the data we speak of so abstractly is very concrete for the people whose lives generated it.

Implications for Regulations and Designs. Participants in our study demonstrated that it is feasible for members of the populace to reason about private computation practices and that they should be given the opportunity to do so. The improvements to acceptability generated by private computation were not universal. Even within the private computation examples participants were shown, the techniques used did not resolve all of their concerns. Participants identified implications of such computations, even proposing some alternative solutions, however it remains the case that the implications of computations are not always clear.

For example, our participants express confidence in the protections of aggregated computations and averages. In practice, this confidence is misplaced [39]. To ensure organizations with less than benevolent intentions do not use this confidence to propagate dark patterns [6], it is necessary to regulate how companies communicate practices such that they include implications and do not obfuscate them. Further, when using techniques that provide probabilistic privacy guarantees, companies must ensure there is a good reason a probabilistic guarantee is appropriate. That is, it must be clear whether it should just always be protected (as said by participants) and if not, why the statistical guarantee provides adequate protection. We acknowledge that it is not necessarily possible, nor practical, to require companies to express all possible implications that could result from a computation they perform. However, whenever possible companies should be required to make explicit what protections are not possible as well as the limitations of the protections being employed.
References

[1] John M Abowd. The US Census Bureau adopts differential privacy. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pages 2867–2867, 2018.

[2] Accountability Act. Health Insurance Portability and Accountability Act of 1996. Public law, 104:191, 1996.

[3] Nitin Agrawal, Reuben Binns, Max Van Kleek, Kim Laine, and Nigel Shadbolt. Exploring Design and Governance Challenges in the Development of Privacy-Preserving Computation. In Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems, pages 1–13, 2021.

[4] Erinn Atwater, Cecylia Bocovich, Urs Hengartner, Ed Lank, and Ian Goldberg. Leading Johnny to Water: Designing for Usability and Trust. In Eleventh Symposium On Usable Privacy and Security (SOUPS 2015), pages 69–88, Ottawa, Canada, 2015. USENIX.

[5] Mark Bergen and Jennifer Surane. Google and Mastercard Cut a Secret Ad Deal to Track Retail Sales. Online, 2018. https://www.bloomberg.com/news/articles/2018-08-30/google-and-mastercard-cut-a-secret-ad-deal-to-track-retail-sales.

[6] Christoph Bösch, Benjamin Erb, Frank Kargl, Henning Kopp, and Stefan Pfattheicher. Tales from the dark side: Privacy dark strategies and privacy dark patterns. Proc. Priv. Enhancing Technol., 2016(4):237–254, 2016.

[7] Brooke Bullek, Stephanie Garboski, Darakhshan J. Mir, and Evan M. Peck. Towards understanding differential privacy: When do people trust randomized response technique? In Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems, CHI ’17, page 3833–3837, New York, NY, USA, 2017. Association for Computing Machinery.

[8] Jan Camenisch and Gregory M Zaverucha. Private Intersection of Certified Sets. In International Conference on Financial Cryptography and Data Security, pages 108–127. Springer, 2009.

[9] Hao Chen, Zhicong Huang, Kim Laine, and Peter Rindal. Labeled PSI from Fully Homomorphic Encryption with Malicious Security. In Proceedings of the 2018 ACM SIGSAC Conference on Computer and Communications Security, pages 1223–1237, New York, New York, USA, 2018. ACM, ACM.

[10] Michelene TH Chi, Miriam Bassok, Matthew W Lewis, Peter Reimann, and Robert Glaser. Self-explanations: How students study and use examples in learning to solve problems. Cognitive science, 13(2):145–182, 1989.

[11] City of Boston. Boston: Closing the Wage Gap. https://www.cityofboston.gov/images_documents/Boston_Closing%20the%20Wage%20Gap_Interventions%20Report_tcm3-41353.pdf, 2013. Accessed 2022-09-23.

[12] Amy Corman, Rachel Canaway, Chris Culnane, and Vanessa Teague. Public Comprehension of Privacy Protections Applied to Health Data Shared for Research: An Australian Cross-Sectional Study. International Journal of Medical Informatics, 167:104859, 2022.

[13] Lorrie Faith Cranor. Necessary but Not Sufficient: Standardized Mechanisms for Privacy Notice and Choice. J. on Telecomm. & High Tech. L., 10:273, 2012.

[14] Emiiliano De Cristofaro, Jihye Kim, and Gene Tsudik. Linear-Complexity Private Set Intersection Protocols Secure in Malicious Model. In International Conference on the Theory and Application of Cryptology and Information Security, pages 213–231. Springer, 2010.

[15] Emiiliano De Cristofaro and Gene Tsudik. Practical Private Set Intersection Protocols with Linear Complexity. In International Conference on Financial Cryptography and Data Security, pages 143–159. Springer, 2010.

[16] Rachel Cummings, Gabriel Kaptchuk, and Elissa M Redmiles. "I need a better description": An Investigation Into User Expectations For Differential Privacy. In Proceedings of the 2021 ACM SIGSAC Conference on Computer and Communications Security, pages 3037–3052, Seoul, South Korea, 2021. ACM.

[17] Emiiliano De Cristofaro, Mark Manulis, and Bertram Poettering. Private Discovery of Common Social Contacts. International Journal of Information Security, 12(1):49–65, 2013.

[18] Cynthia Dwork, Frank McSherry, Kobbi Nissim, and Adam D. Smith. Calibrating Noise to Sensitivity in Private Data Analysis. In Theory of Cryptography, Third Theory of Cryptography Conference, TCC 2006, March 4-7, 2006, Proceedings, pages 265–284, New York, USA, 2006. Springer.

[19] Benjamin Fabian, Tatiana Ermakova, and Tino Lentz. Large-Scale Readability Analysis of Privacy Policies. In Proceedings of the International Conference on Web Intelligence, pages 18–25, 2017.

[20] Casey Fiesler and Blake Hallinan. “We Are the Product” Public Reactions to Online Data Sharing and Privacy Controversies in the Media. In Proceedings of the 2018
[21] Daniel Franzen, Saskia Nuñez von Voigt, Peter Sörries, Florian Tschorsch, and Claudia Müller-Birn. “Am I Private and If So, how Many?”-Communicating Privacy Guarantees of Differential Privacy with Risk Communication Formats. arXiv preprint arXiv:2208.10820, 2022.

[22] Matt Fredrikson, Somesh Jha, and Thomas Ristenpart. Model Inversion Attacks that Exploit Confidence Information and Basic Countermeasures. In Proceedings of the 22nd ACM SIGSAC Conference on Computer and Communications Security, October 12-16, 2015, pages 1322–1333, Denver, CO, USA, 2015. ACM.

[23] Michael J. Freedman, Kobbi Nissim, and Benny Pinkas. Efficient Private Matching and Set Intersection. In Advances in Cryptology - EUROCRYPT 2004, International Conference on the Theory and Applications of Cryptographic Techniques, May 2-6, 2004. Proceedings, pages 1–19, Interlaken, Switzerland, 2004. IACR.

[24] Karan Ganju, Qi Wang, Wei Yang, Carl A. Gunter, and Nikita Borisov. Property Inference Attacks on Fully Connected Neural Networks using Permutation Invariant Representations. In Proceedings of the 2018 ACM SIGSAC Conference on Computer and Communications Security, CCS 2018, October 15-19, 2018, pages 619–633, Toronto, Canada, 2018. ACM.

[25] Oded Goldreich, Silvio Micali, and Avi Wigderson. How to Play any Mental Game or A Completeness Theorem for Protocols with Honest Majority. In Proceedings of the 19th Annual ACM Symposium on Theory of Computing, 1987, pages 218–229, New York, USA, 1987. ACM.

[26] Adam Groce, Peter Rindal, and Mike Rosulek. Cheaper Private Set Intersection via Differentially Private Leakage. Proceedings on Privacy Enhancing Technologies, 2019(3), 2019.

[27] Briland Hitaj, Giuseppe Ateniese, and Fernando Pérez-Cruz. Deep Models Under the GAN: Information Leakage from Collaborative Deep Learning. In Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security, CCS 2017, October 30 - November 03, 2017, pages 603–618, Dallas, TX, USA, 2017. ACM.

[28] Karen Holtzblatt and Hugh Beyer. Contextual Design: Defining Customer-Centered Systems. Elsevier, 1997.

[29] Thomas Humphries, Matthew Rafuse, Lindsey Tulloch, Simon Oya, Ian Goldberg, Urs Hengartner, and Florian Kerschbaum. Investigating Membership Inference Attacks under Data Dependencies. CoRR, abs/2010.12112, 2020.

[30] Bailey Kacsmar, Kyle Tilbury, Mitu Mazmudar, and Florian Kerschbaum. Caring about Sharing: User Perceptions of Multiparty Data Sharing. In 31st USENIX Security Symposium (USENIX Security 22), Boston, MA, August 2022. USENIX Association.

[31] Ruogu Kang, Laura Dabbish, Nathaniel Fruchter, and Sara Kiesler. “My Data Just Goes Everywhere:” User Mental Models of the Internet and Implications for Privacy and Security. In Eleventh Symposium on Usable Privacy and Security (SOUPS 2015), pages 39–52, 2015.

[32] Farzaneh Karegar, Ala Sarah Alaqr, and Simone Fischer-Hübner. Exploring User-Suitable metaphors for differentially private data analyses. In Eighteenth Symposium on Usable Privacy and Security (SOUPS 2022), pages 175–193, Boston, MA, August 2022. USENIX Association.

[33] Jiro Kawakita. The Original KJ Method. Tokyo: Kawakita Research Institute, 5, 1991.

[34] Lea Kissner and Dawn Song. Privacy-preserving set operations. In Annual International Cryptology Conference, pages 241–257. Springer, 2005.

[35] Patrick Kühtreiber, Viktoriya Pak, and Delphine Reinhart. Replication: The Effect of Differential Privacy Communication on German Users’ Comprehension and Data Sharing Attitudes. In Eighteenth Symposium on Usable Privacy and Security (SOUPS 2022), pages 117–134, 2022.

[36] Patrick Kühtreiber and Delphine Reinhart. Usable Differential Privacy for the Internet-of-Things. In 2021 IEEE International Conference on Pervasive Computing and Communications Workshops and other Affiliated Events (PerCom Workshops), pages 426–427. IEEE, 2021.

[37] Thomas Linden, Rishabh Khandelwal, Hamza Harkous, and Kassem Fawaz. The Privacy Policy Landscape After the GDPR. arXiv preprint arXiv:1809.08396, 2018.

[38] Maureen Mahoney. California Consumer Privacy Act: Are Consumers’ Digital Rights Protected. Technical report, Technical Report. Consumer Reports., 2020. https://advocacy.consumerreports.org/press_release/consumer-reports-study-finds-significant-obstacles-to-exercising-california-privacy-rights/.
[39] Francesco M. Malvestuto, Mauro Mezzini, and Marina Moscarini. Auditing sum-queries to make a statistical database secure. *ACM Trans. Inf. Syst. Secur.*, 9(1):31–60, Feb 2006.

[40] Peter Mayer, Yixin Zou, Florian Schaub, and Adam J Aviv. “Now I’m a Bit Angry:” Individuals’ Awareness, Perception, and Responses to Data Breaches that Affected Them. In *The Thirtieth USENIX Security Symposium* 2021, 2021.

[41] Aleecia M McDonald and Lorrie Faith Cranor. Americans’ Attitudes About Internet Behavioral Advertising Practices. In *Proceedings of the Ninth Annual ACM Workshop on Privacy in the Electronic Society*, pages 63–72, 2010.

[42] Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Agüera y Arcas. Communication-Efficient Learning of Deep Networks from Decentralized Data. In *Proceedings of the 20th International Conference on Artificial Intelligence and Statistics, AISTATS 2017*, 20-22 April 2017, pages 1273–1282, Fort Lauderdale, USA, 2017. ACM.

[43] Priyanka Nanayakkara, Johes Bater, Xi He, Jessica Hullman, and Jennie Rogers. Visualizing Privacy-Utility Trade-Offs in Differentially Private Data Releases. *Proceedings on Privacy Enhancing Technologies*, 2:601–618, 2022.

[44] Helen Nissenbaum. Contextual Integrity Up and Down the Data Food Chain. *Theoretical Inquiries in Law*, 20(1):221–256, 2019.

[45] Thomas B Norton. The Non-Contractual Nature of Privacy Policies and a New Critique of the Notice and Choice Privacy Protection Model. *Fordham Intell. Prop., Media & Ent. L.J.*, 27:181, 2016.

[46] Maggie Oates, Yama Ahmadullah, Abigail Marsh, Chelse Swoopes, Shikun Zhang, Rebecca Balebako, and Lorrie Faith Cranor. Turtles, Locks, and Bathrooms: Understanding Mental Models of Privacy Through Illustration. *Proceedings on Privacy Enhancing Technologies*, 2018(4):5–32, 2018.

[47] Sean O’Connor, Ryan Nurwono, and Eleanor Birrell. (Un) clear and (In) conspicuous: The Right to Opt-Out of Sale Under CCPA. *arXiv preprint arXiv:2009.07884*, 2020.

[48] Office of the Privacy Commissioner of Canada. PIPEDA in brief. https://www.priv.gc.ca/en/privacy-topics/privacy-laws-in-canada/the-personal-information-protection-and-electronic-documents-act-pipedapipeda_brief/, 2019. Accessed 2019-06-18.

[49] Benny Pinkas, Thomas Schneider, Gil Segev, and Michael Zohner. Phasing: Private set intersection using permutation-based hashing. In *24th USENIX Security Symposium (USENIX Security 15)*, pages 515–530, Washington, D.C., August 2015. USENIX Association.

[50] Benny Pinkas, Thomas Schneider, Christian Weimert, and Udi Wieder. Efficient Circuit-Based PSI via Cuckoo Hashing. In Jesper Buus Nielsen and Vincent Rijmen, editors, *Advances in Cryptology – EUROCRYPT 2018*, pages 125–157, Cham, 2018. Springer International Publishing.

[51] Benny Pinkas, Thomas Schneider, and Michael Zohner. Scalable private set intersection based on ot extension. *ACM Trans. Priv. Secur.*, 21(2), Jan 2018.

[52] Lucy Qin, Andrei Lapets, Frederick Jansen, Peter Flockhart, Kinan Al Albab, Ira Globus-Harris, Shannon Roberts, and Mayank Varia. From usability to secure computing and back again. In *Fifteenth Symposium on Usable Privacy and Security (SOUPS 2019)*, pages 191–210, Santa Clara, CA, August 2019. USENIX Association.

[53] Emilee Rader. Awareness of Behavioral Tracking and Information Privacy Concern in Facebook and Google. In *Tenth Symposium On Usable Privacy and Security 2014*, pages 51–67, 2014.

[54] Elissa M Redmiles, Ziyun Zhu, Sean Kross, Dhruv Kuchhal, Tudor Dumitras, and Michelle L Mazurek. Asking for a Friend: Evaluating Response Biases in Security User Studies. In *Proceedings of the 2018 ACM SIGSAC Conference on Computer and Communications Security*, pages 1238–1255, New York, New York, USA, 2018. ACM, ACM.

[55] Karen Renaud, Melanie Volkamer, and Arne Renkema-Padmos. Why doesn’t Jane protect her privacy? In *International Symposium on Privacy Enhancing Technologies Symposium*, pages 244–262, Amsterdam, Netherlands, 2014. Springer.

[56] John A Rothchild. Against Notice and Choice: The Manifest Failure of the Proceduralist Paradigm to Protect Privacy Online (Or Anywhere Else). *Clev. St. L. Rev.*, 66:559, 2017.

[57] Florian Schaub, Rebecca Balebako, and Lorrie Faith Cranor. Designing effective privacy notices and controls. *IEEE Internet Computing*, 21(3):70–77, 2017.

[58] Jonathan Schulz, Duman Bahrami-Rad, Jonathan Beauchamp, and Joseph Henrich. The Origins of WEIRD Psychology. Available at SSRN 3201031, 2018.
[59] Raymond Scupin. The KJ Method: A Technique for Analyzing Data Derived from Japanese Ethnology. Human Organization, 56(2):233–237, 1997.

[60] Irina Shklovski, Scott D Mainwaring, Halla Hrud Skúladóttir, and Höskuldur Borgthorsson. Leakiness and Creepiness in App Space: Perceptions of Privacy and Mobile App Use. In Proceedings of the 32nd annual ACM conference on Human factors in computing systems, pages 2347–2356, New York, New York, USA, 2014. ACM, ACM.

[61] Reza Shokri, Marco Stronati, Congzheng Song, and Vitaly Shmatikov. Membership Inference Attacks Against Machine Learning Models. In 2017 Symposium on Security and Privacy, SP 2017, May 22-26, 2017, pages 3–18, San Jose, USA, 2017. IEEE.

[62] Jesper Simonsen and Toni Robertson. Routledge International Handbook of Participatory Design, volume 711. Routledge New York, 2013.

[63] Mary Anne Smart, Dhruv Sood, and Kristin Vaccaro. Understanding Risks of Privacy Theater with Differential Privacy. In CSCW 2022, 2022.

[64] State of California Department of Justice. California Consumer Privacy Act (CCPA). https://oag.ca.gov/privacy/ccpa, 2018. Accessed 2022-09-04.

[65] Peter Story, Daniel Smullen, Xaying Yao, Alessandro Acquisti, Lorrie Faith Cranor, Norman Sadeh, and Florian Schaub. Awareness, Adoption, and Misconceptions of Web Privacy Tools. Proceedings on Privacy Enhancing Technologies, 3:308–333, 2021.

[66] Stacey Truex, Nathalie Baracaldo, Ali Anwar, Thomas Steinke, Heiko Ludwig, Rui Zhang, and Yi Zhou. A Hybrid Approach to Privacy-Preserving Federated Learning. In Proceedings of the 12th ACM Workshop on Artificial Intelligence and Security, AISec’19, page 1–11, New York, NY, USA, 2019. Association for Computing Machinery.

[67] Stacey Truex, Nathalie Baracaldo, Ali Anwar, Thomas Steinke, Heiko Ludwig, Rui Zhang, and Yi Zhou. A Hybrid Approach to Privacy-Preserving Federated Learning. In Proceedings of the 12th ACM Workshop on Artificial Intelligence and Security, AISec’19, page 1–11, New York, NY, USA, 2019. Association for Computing Machinery.

[68] U.S. Federal Trade Commission. Children’s Online Privacy Protection Rule (“COPPA”). https://www.ftc.gov/legal-library/browse/rules/childrens-online-privacy-protection-rule-coppa, 2022. Accessed 2022-09-04.

[69] Paul Voigt and Axel Von dem Bussche. The EU General Data Protection Regulation (GDPR). A Practical Guide, 1st Ed., Cham: Springer International Publishing, 2017.

[70] Justin Wu and Daniel Zappala. When is a tree really a truck? Exploring Mental Models of Encryption. In Fourteenth Symposium on Usable Privacy and Security (SOUPS 2018), pages 395–409, 2018.

[71] Aiping Xiong, Tianhao Wang, Ninghui Li, and Somesh Jha. Towards effective differential privacy communication for users’ data sharing decision and comprehension. In 2020 IEEE Symposium on Security and Privacy (SP), pages 392–410. IEEE, 2020.

[72] Andrew Chi-Chih Yao. How to Generate and Exchange Secrets (Extended Abstract). In 27th Annual Symposium on Foundations of Computer Science, 27-29 October 1986, pages 162–167, Toronto, Canada, 1986. IEEE.

[73] Samuel Yeom, Irene Giacomelli, Matt Fredrikson, and Somesh Jha. Privacy Risk in Machine Learning: Analyzing the Connection to Overfitting. In 31st Computer Security Foundations Symposium, CSF 2018, July 9-12, 2018, pages 268–282, Oxford, United Kingdom, 2018. IEEE.
A Additional Table

We include Table 2 for reference. The table consists of examples from participants at the start of the study that they thought could be settings for private computation.

Table 2: The above includes examples provided by participants in response to the prompt for “an example of a computation where the result can be made public, but the numbers used to determine the result are sensitive and need to stay private”. Only responses that participants did not change their minds about are included.

| Example data                       | Private Data           | Public Output                      |
|------------------------------------|------------------------|------------------------------------|
| (P1) Individual income, education completed | Individuals’ incomes | Mean income by education          |
| (P2) Voting                        | Individuals’ votes     | Result counts                       |
| (P3) Research study                | Participants           | Study data                         |
| (P5) Voting                        | Individuals’ votes     | Eligible voters                    |
| (P6) Income, location              | Households’ income     | Mean income in a region            |
| (P7) Salaries                      | Individuals’ salary    | Average salary                     |
| (P9) Financial organizations’ data | Customer data          | Fianical trends                    |
| (P10) Telescope data               | Raw data               | Post-processed data                |
| (P12) Personal data                | i.e. age, demographics | Averages                           |
| (P13) Netflix views                | Viewer distributions   | Report on top service              |
| (P17) Salaries                     | Individuals’ salary    | Average salary                     |
| (P18) Political surveys            | Individual responses   | Aggregated conclusions             |
| (P19) Profits                      | Beneficiaries          | Donations                          |
| (P21) Elections                    | Individuals’ responses | Poll numbers                       |
| (P21) Infection disease studies    | Collected data         | Results                            |

B Interview Guide

Note that the order of the terms (a-h), the four scenarios (wage equity, census data, ad conversion, contact discovery), the four cases (one to four), and the examples within each case (a to do) were randomized.

B.1 Welcome

Welcome. Today we are going to be talking about a topic that may be new to you. We’re currently studying public sentiments and understanding of novel data science techniques. We’re interested in learning about what people expect and what questions they want addressed if their data is being used for data science by a company. The interview process helps us to understand these expectations and based on them, to make design recommendations for other researchers and policy makers. Please let us know at any point if you have questions. Before we start, I just want to make sure you have a something to write with/on, pen and paper. Throughout the interview, we’re going to go through four types of questions, some general, some about terminology, some about types of data sharing, and some about explaining how data is used. On average I expect this interview to take 60 minutes. Do you have any questions or concerns before we start?

B.2 Warm-up/Baseline questions

To get us started, I’m going to ask you a general question on the topic. For the question, just state as many answers as come to mind and let me know when you’re done.

1. Please list some of the ways that you expect companies use data about you and others.

B.3 Terms

For the next section of this interview, we are going to talk about approaches to data sharing that focus on ‘how’ the data is shared. We are going to go through a series of terms and I’ll ask you if you are familiar with them, and some follow up questions.

1. Terms:
   (a) Private Computation
   (b) Encryption
   (c) Hashing
(d) Multi-party Computation
(e) Differential Privacy
(f) Federated Learning
(g) Private Machine Learning
(h) Secure Computation

2. Have you come across the term [(a) through (h)] before?
   (a) (if yes) Where have you come across the term before?
   (b) (if yes) What kind of guarantees do you think it provides to individuals? Some examples?
   (c) (if yes) What do you think the purpose or goal is for a company using this?
   (d) Please try to define the term in your own words

B.4 Describing Private Computation

We’re now going to introduce the term private computation.

• A **computation** is just a calculation (generally in math). For instance, determining the largest number from a list, determining the average, determining a sum.

• A **private computation**, is a computation that tries to limit the information revealed by the result. It attempts to perform a computation (such as an average, sum, max), and share the result without anyone learning the values used to find the result.

1. What do you think is an example of a computation where the result can be made public, but the numbers used to determine the result are sensitive and need to stay private? Follow up: what is sensitive and what is not in the example.
2. How would you describe private computation in your own words?

B.5 Private Computation Scenarios

We are now going to talk about some different ways companies can work with client data.

I. Wage equity: An organization aims to identify salary inequities across demographics. They reach out to individuals and employment organizations about their salary data. The organization conducts an analysis over the salary data and produces a report on salary inequities. The organization acquires the data for the analysis such that... How acceptable is the organization’s goal? Scale: (completely unacc, unacceptable, neutral, acceptable, completely acceptable)
   (a) ...salary data is shared directly. They receive the salary information of individuals from the individuals or employers via a web-based tool.
   (b) ...salary data is submitted in a modified form privately (with technical and legal protections) via a web-based multi-party computation (MPC) tool. The technical protections prevent the identification of individuals’ salary input from the final report. It also protects those who contributed their salary information from being connected to the salary information they provided (though does not prevent it from being known that they were a contributor). Using this technique can be more expensive for the analysis and they cannot use the data for any other purpose.

II. Census data is acquired from citizens of the country by the governing body. It includes information with respect to their age, gender, occupation, income, place of residence. The governing body analyses the data it acquires to inform policies and resource management. It can also make the results of the census available to researchers or the public by... How acceptable is the organization’s goal? Scale: (completely unacc, unacceptable, neutral, acceptable, completely acceptable)
   (a) allowing aggregate/statistical queries (e.g. averages, sums, etc.) over the original data.
   (b) allowing any query, but restricting individuals making queries from performing queries that allow them to make inferences/learn more information than is permitted. This means that some questions cannot be answered by querying the data.

III. Ad conversion: An online ad company wants to determine whether ads shown to its users lead to sales in physical stores. They reach out to a credit card company, which has transaction data for physical stores to compute whether there are purchases connected to their ads. The two companies perform the computation such that... How acceptable is the organization’s goal? Scale: (completely unacc, unacceptable, neutral, acceptable, completely acceptable)
   (a) ...they each share their datasets. The credit card company shares the purchase data in physical stores and the online company computes the correlation to online identities locations and online ad views.
   (b) ...the credit card company shares a modified version of their records. The credit card company shares the modified data such that the online company can only identify the financial records that correspond to its users. That is, the information on the other credit card clients (that do not use the online service) is not available to the online company. Using this technique can be more expensive for the company and they cannot use the data for any other purpose.
IV. Contact discovery: A social media app wants to connect users that are already contacts with one another. The social media app has a list of contact information (its users) and the new user has a list of contact information (their friends etc). The app wants to determine the common contacts between the new user and the existing app users (the intersection). Note that not all of the new users contacts may use the social media app and not all users of the app are contacts with the new user. The social media app can connect the new user to existing users by performing a computation such that... How acceptable is the organization’s’ goal? Scale: (completely unacc, unacceptable, neutral, acceptable, completely acceptable)

(a) ...the new user shares all their personal contact information with the social media app.
(b) ...the new user shares a modified version of their personal contact information. The new user shares the modified data such that the social media company can only identify the new users’ contacts that already use the social media app.
That is, the other contacts (who do not use the social media app) are not available to the social media app. Using this technique can be more expensive for the company and they cannot use the data for any other purpose.

For each of [A], [B], [C], and [D], the following were asked:
1. How acceptable is it if the company uses (a)? Explain (completely unacc, unacceptable, neutral, acceptable, completely acceptable)
2. How acceptable is it if the company uses (b)? Explain (completely unacc, unacceptable, neutral, acceptable, completely acceptable)
3. What differences do you expect there should be (if any) if a company chooses to use (b) instead of (a)...
   (a) in general?
   (b) in terms of how companies inform their clients that their data is being used?
   (c) in terms of what companies inform their clients about when their data is being used?
4. How feasible/possible do you think it is for a company to use (b) instead of (a)
5. How should a company be explaining the technique (b) to their clients if they use it?

B.6 Potential Information Revealed

Case 1: One of the participating companies will additionally be able to learn which specific records in the computed result correspond to you. How acceptable is it if the records that correspond to you are...
   a) ...your salary information? Explain.
   b) ...your credit history (e.g., credit score, mortgage status)? Explain.
   c) ...your location history (e.g., coordinates corresponding to your home, place of employment, etc.) Explain.
   d) ...your genetic markers (e.g., for heart disease, cancer, etc.)? Explain.

Case 2: One of the participating companies will additionally be able to learn if records of you were used to perform the computation. How acceptable is it if the records they learn correspond to you are in a dataset of...
   a) ...low-income households (and thus learn that you are in a low income household)? Explain.
   b) ...dating app members (and thus learn that you use that dating app)? Explain.
   c) ...people with a specific health condition e.g., diabetic, high-blood pressure, autoimmune diseases (and thus learn that you have that specific health condition)? Explain.
   d) ...frequent drug users e.g., alcohol, marijuana, others (and thus learn that you are a frequent user of that drug)? Explain.

Case 3: One of the participating companies will learn properties for groups. A group could be people with glasses or any other attribute corresponding to a group of people such as demographics. How acceptable is it if a company can learn, for example...
   a) ...glasses owners prefer shopping online? Explain.
   b) ...women prefer shopping online? Explain.
   c) ...glasses owners have poorer spending habits than non-glasses owners? Explain.
   d) ...women have poorer spending habits than non-women? Explain.

Case 4: When two companies perform the private computation, if one of the participating companies possesses other additional information (e.g. statistics) they can infer the exact value of a record used in the computation. How acceptable is it if a company can always learn whether an exact record was contributed by the other organization? Explain.
   a) How acceptable is it if a company can always learn whether an exact record was contributed by the other organization? Explain.
b) Is it more or less acceptable if a company can accurately learn the record contributed by a different company only 75% of the time? Explain.
c) ...50% of the time? Explain.
d) ...25% of the time? Explain.
e) To you, at what point (percentage) does this become unacceptable/acceptable? Explain.

Additional Information:
- How does it impact the acceptability if additional information has to be known to learn the values?
- How does the information that needs to be known influence the acceptability?
- How does the likelihood the additional information is known influence the acceptability?

B.7 General Responses

1. In general, how do you think companies should be communicating to their customers/clients about how they use customer/client data in general?
2. In general, how do you think companies should be communicating to their customers/clients about how they use customer/client data if they use private computation for the process?
3. In general, what do you think are companies responsibilities when using your data in these computations? Follow up depending on response: in terms of data protection responsibilities?

B.8 Participant Explanations

Prompt. The last thing we are going to do is an exercise called co-design. Even though you may have just learned about these techniques, we want you to think about how you would communicate these techniques to someone. There are no right or wrong answers. Imagine you work for a company that wants to use private computation. How would you communicate these practices to your clients? You can draw, write, verbally explain, etc.

Compare Show participant the previous suggestion.
- What would they add/remove to theirs based on it.
- What would they add/remove to the previous one.
- What is their final version they put forth after having considered the previous one.

B.9 Closing

Includes feedback and appreciation.