“Am I Private and If So, how Many?” — Using Risk Communication Formats for Making Differential Privacy Understandable

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Mobility data is essential for cities and communities to identify areas for necessary improvement. Data collected by mobility providers already contains all the information necessary, but privacy of the individuals needs to be preserved. Differential privacy (DP) defines a mathematical property which guarantees that certain limits of privacy are preserved while sharing such data, but its functionality and privacy protection are difficult to explain to laypeople. In this paper, we adapt risk communication formats in conjunction with a model for the privacy risks of DP. The result are privacy notifications which explain the risk to an individual’s privacy when using DP, rather than DP’s functionality. We evaluate these novel privacy communication formats in a crowdsourced study. We find that they perform similarly to the best performing DP communications used currently in terms of objective understanding, but did not make our participants as confident in their understanding. We also discovered an influence, similar to the Dunning-Kruger effect, of the statistical numeracy on the effectiveness of some of our privacy communication formats and the DP communication format used currently. These results generate hypotheses in multiple directions, for example, toward the use of risk visualization to improve the understandability of our formats or toward adaptive user interfaces which tailor the risk communication to the characteristics of the reader.

CCS Concepts: • Security and privacy → Usability in security and privacy; Data anonymization and sanitization; • General and reference → Surveys and overviews; • Human-centered computing → Empirical studies in visualization.

Additional Key Words and Phrases: communication, privacy, privacy risk, differential privacy

1 INTRODUCTION

We generate a large amount of mobility data daily, for example, when searching online for routes on public transport or when purchasing tickets.

Due to the ubiquitousness of smartphones, collecting location and mobility data has become a quasi-standard for many applications, and prediction algorithms use the data collected for various purposes (e.g., [7, 28, 45]).

At the same time, although laypeople are often unaware of this situation [8, 50], location data are very sensitive [34]. They can be used to identify locations of interest (e.g., home address), reveal daily routines (e.g., doing exercises), show social relationships (e.g., collecting a child from daycare, meeting a friend) and might also disclose certain health conditions by collecting repeated visits to a medical facility. The most privacy-aware choice would be not to share location data, which comes with personal restrictions, since many services cannot be used without such access.

However, mobility data is also essential for the development of urban areas, for example, to identify where public transport can be improved, bicycle lanes can be added or how new pedestrian zones might influence a neighborhood. Here, communities have to rely on either data donations by individuals [32] or a collaboration with a local public transport provider which already collects data as part of their service.
What we have described is a typical trade-off. On the one hand, we need mobility data to further develop our society to meet current challenges, especially for fighting climate change [44, 66]; on the other hand, we urge companies and governments to protect our privacy better.

Anonymization techniques are necessary in order to make available mobility data usable without compromising privacy. Policies, such as the General Data Protection Regulation (GDPR), support this by requiring that data controllers “shall implement appropriate technical and organizational measures” as part of “data protection by design and by default”\(^1\). However, such regulations do not define what “data protection by design” means. Research has shown, for example, that simply removing user identifiers is insufficient for anonymizing data adequately. The combination of multiple data sets can still lead to re-identification and, thus, the disclosure of sensitive information (e.g., [43]).

The concept of Differential Privacy (DP) was proposed by Dwork [23], to defend against such re-identification. It refers to the idea that the output of a computation should not reveal anything (or at least verifiably little) about an individual. It is a mathematically rigorous definition of privacy that can provide people with guarantees regarding the risk of re-identification [21]. Several techniques have been developed (e.g., PATE for machine learning [46]) over the last years that realize this idea by adding carefully constrained noise to the results of computations [5]. This approach offers a balance between the accuracy of the data and the privacy guaranteed in DP. The parameter \(\epsilon\) acts as a privacy budget and governs this balance.

Now, one might argue that DP, as a technical concept, might be sufficient for solving the aforementioned trade-off and ensuring data protection by design. However, we argue that in addition to a suitable privacy-enhancing technology, we need to involve the people who share their anonymized data. Companies, such as Apple and Google, or governmental agencies, such as the US Census Bureau, already employ DP (cf. [21]); however, they do this on their own terms. When using DP, we argue, people need to comprehend what it means to use DP in order to provide an informed consent. So far, individuals have been made aware of the use of DP by explaining some aspects of its functionality, but organizations (or research) omit explaining the chosen value for the parameter \(\epsilon\) (e.g., [19]). However, the privacy of DP depends on the choice of this parameter. In our research, we take the first step to close this gap. We propose using risk communication formats to convey the associated risk of sharing personal data to laypeople. As opposed to existing research that explains the functionality of DP (e.g., [64]), we adapt empirically validated research from the medical domain, where risk communication is an essential part of similar education and decision processes.

In our research, we compare suitable risk communication formats to existing best practices and investigate the understandability of these formats, i.e., the subjective and objective understanding. Our research question is: What risk communication formats support laypeople’s understanding of the privacy guarantees provided by Differential Privacy best?

Utilizing our research, we want to enable people to become aware of the consequences of using DP (with a particular parameter \(\epsilon\)) by describing the risk to their privacy. Only after understanding the potential consequences of data sharing can a person consciously decide to donate the data to improve the greater community. Thus, we make the following contributions:

- We propose the usage of risk communication formats as a means to communicate the privacy risks of DP in an understandable way.
- We derive suitable, empirically validated risk communication formats from existing research in the medical domain and combine them with risk values derived from an existing mathematical model of DP (cf. [39]), representing real-world, accurate privacy risks of DP.
- We evaluate the understandability of these notifications in a crowdsourced user study.

\(^1\)For more information, please visit https://gdpr-info.eu/art-25-gdpr/ and https://gdpr-info.eu/recitals/no-42/.
• We suggest the risk communication formats for contextual anonymity, i.e., the situated adaptation of privacy preferences.

The remainder of this paper is structured in the following way. We provide a brief overview of the current state of DP in Section 2 and argue that a novel communication concept for DP is necessary. We substantiate this by discussing recent research into the communication of DP and survey suitable formats from medical risk communication. Section 3 details how we design the proposed novel risk communication formats and in Section 4, we describe the design of the study to evaluate their understandability. The results are presented in Section 5 and discussed in Section 6. We conclude in Section 7 with limitations and future work.

2 THE ISSUE WITH COMMUNICATING DIFFERENTIAL PRIVACY

The design and impact of privacy notices in general is a widely researched field of work, for example [16, 49]. The communication of privacy risks when using DP, however, presents specific challenges and opportunities, which have not been studied extensively so far. In the following section, we review the existing approaches on communicating DP to individuals (cf. Section 2.2). We then extend our focus into the medical domain that has studied the opportunities and limitations of risk communication over the last twenty years (cf. Section 2.3). Before we dive deeper into these topics, we establish a shared terminology and provide a short introduction to DP (cf. Section 2.1).

2.1 Differential Privacy

Differential privacy is a mathematical property that aims to protect the privacy of individuals when querying information from a data set stored in a statistical database [23]. In the following, we use the term individual to emphasize that the data set holds personal and potentially sensitive information about people. We assume that these individuals are laypeople who have a limited knowledge of privacy measures and technologies used, and might have different levels of statistical numeracy. Accordingly, privacy risks must be communicated to these individuals with particular care and circumspection.

Additionally, we consider two groups of stakeholders, namely, data owners and data consumers. Data owners are companies or service providers that collect individuals’ data. Data consumers are public institutions, companies or other third parties using this data for analytics, i.e., statistical analysis.

In the context of mobility data, for example, individuals are the users of a particular mobility app. While using the mobility app, the service provider, i.e., the data owner, already collects personal data (e.g., the trips taken) as part of the service. However, as laid out in the introduction, there are many relevant purposes for sharing aggregate statistics about this data with third parties, i.e., data consumers, such as the local municipality. When sharing data based on individuals with data consumers, a DP mechanism can be employed to preserve the privacy of individuals included against the data consumer. The DP mechanism used modifies the results of the statistics to “hide” the data of each individual and its influence on the outcome, while maintaining the overall outcome of the analysis.

The underlying principle of DP is to limit the impact of a single individual on the analysis outcome. More specifically, the presence or absence of an individual’s data must not lead to a significantly different outcome of the analysis. Formally, assume two data sets $D_1$ and $D_2$ differing in exactly one entry. A function $f$ provides $\epsilon$-DP if for all such $D_1$ and $D_2$, all outcomes $S \subseteq \text{Range}(f)$ satisfy

$$P[f(D_1) \in S] \leq e^\epsilon \cdot P[f(D_2) \in S].$$
The core component of DP is the privacy loss parameter $\epsilon$ that bounds how far an outcome of a data set is allowed to deviate when adding or removing one single individual.

We illustrate this property in Figure 1 and explain it in more detail next. We consider two data sets $D_1$ and $D_2$ that differ only in whether Alice has contributed her data (the red circle) or not. Using DP to protect Alice, it is required that the resulting outcome of an analysis should be approximately the same independently of Alice’s contribution. To achieve this, the DP mechanism adds carefully tuned random noise to the outcome, which results in a randomized outcome that is close to the actual value without DP [62]. In Figure 1, the distributions (red: with Alice, blue: without Alice) represent the probability of a certain outcome of the statistics. The factor $e^\epsilon$ bounds the ratio between these probability distributions, i.e., how similar the randomized outcomes of $D_1$ and $D_2$ have to be and, thus, determines the maximum influence of a single individual’s data point on the outcome. Since the probabilities of $D_1$ and $D_2$ are similar (only differing by the ratio that is set by $\epsilon$), the data consumer cannot be certain whether $D_1$ or $D_2$ was used to generate the final outcome and, therefore, whether Alice is included in the data set or not.

We can differentiate two edge cases to illustrate the trade-off between privacy protection and accuracy of the result: For $\epsilon = 0$, the definition requires the outcome to be exactly the same probability for both data sets ($P[f(D_1)] = P[f(D_2)]$). In this case, the two probability distributions would be identical and, thus, lie on top of each other. Therefore, Alice’s data is irrelevant for the outcome. The same argument holds for any individual, since DP requires this property not just for Alice but for any two data sets that differ by one entry. Consequently, any results obtained could also be obtained from the empty data set. Although this leads to perfect privacy, the outcome of $f$ is completely useless for any statistic purpose [62]. However, even if $\epsilon = 0$, a data consumer can still randomly guess whether Alice contributed her data or not, and, thus, a re-identification risk remains.

At the other extreme, i.e., if $\epsilon$ is very large, DP is already achieved with very little noise. The outcome of DP is very close to the actual value, almost as if no DP was used. In this case, DP provides a high accuracy but low privacy.

In order to balance between the accuracy of the outcome and privacy protection, we need to choose a reasonable small $\epsilon > 0$ that results in an outcome of $f$ which is “almost” independent
regarding whether a single individual is in the data set or not but, at the same time, still accurately representing the body of the data as a whole.

In summary, when we carefully choose the parameter $\varepsilon$, DP can be a valuable tool for providing *data protection by design*. By contrast, with a less careful choice of $\varepsilon$, the effectiveness of the privacy protection offered by DP can be reduced or even completely suppressed. For this reason, the value used for $\varepsilon$ and the rationale for this choice is essential information for evaluating the privacy protection offered by DP. Thus, providing this information to users is essential for making privacy decisions. In the next section, we give an overview of existing approaches to communicate DP.

2.2 Communicating Differential Privacy

The goal of risk communication for DP is to inform laypeople about potential privacy risks and, in turn, facilitate informed consent. According to Schaub et al. [49], privacy notifications need to comply with three main requirements to enable informed consent: (1) the notification is relevant in the current context, (2) it offers options for a decision and (3) it is understandable.

We will not consider the first requirement in detail, since there is not enough research into DP in general, yet. Therefore, we have fixed the context described in Section 2.1 for our evaluation. The second requirement is mostly independent of the privacy-preserving technology used. Any DP-specific options, such as the possible choice of a specific $\varepsilon$ by the user, are left for future research.

The third requirement, however, is highly specific to the DP mechanism. The DP communication is challenged to explain DP’s rigorous mathematical definition in an understandable way such that individuals can profit from the strong privacy guarantees. In particular, privacy notices about DP should enable individuals to understand the guaranteed limit of their privacy risks based on the specific choice of $\varepsilon$ in their particular situation.

Differential privacy is already used in practice [1, 20, 26]. There have also been various attempts to explain the DP mechanism to individuals. However, these attempts have led to mixed feedback. The US Census Bureau, for example, used DP and experienced that people did not understand the functioning of DP or even the necessity of using DP, even though this information was offered. In other cases, companies who use DP do not provide the necessary information in an easily accessible way, for example, the value of the parameter $\varepsilon$ or the rationale for choosing this value (cf. [65]). Without this information, the evaluation of the privacy protection offered by DP is not possible for an individual, even if they understand the property of DP.

We assume that this situation can be attributed to two factors. On the one hand, the mathematical property of DP is difficult to explain to laypeople. Best practices do not yet exist because DP is still an emerging technology. On the other hand, the companies designing the explanations currently have no incentive to explain DP in detail, as their main goal is to collect as much data as possible. The use of DP might serve as a fig leaf rather than as a commitment to privacy protection. Thus, independent research is needed to understand better how suitable explanations can support individuals in their understanding of DP as a protection mechanism. There have already been a few studies that compare the effectiveness of communicating DP to laypeople, which we summarize in the following.

Bullek et al. [15] conducted a study to explain DP using the randomized response technique [60] as a metaphor. Instead of modifying the data in the data set after the study, the randomized response technique satisfies DP during data collection by instructing participants to answer sensitive questions according to the following procedure. For each question, the participants spin a *Wheel of Fortune*-like visualization which displays one of three instructions: the participants are asked to

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2 For more information, please visit: https://nypost.com/2021/08/26/elsie-elier-surprised-when-one-person-nebraska-town-doubles-in-census/, accessed 2021-10-06.

3 For more information, please visit: https://www.nytimes.com/2018/12/05/upshot/to-reduce-privacy-risks-the-census-plans-to-report-less-accurate-data.html, accessed 2021-10-06.
either answer truthfully or to answer “Yes” or “No” as indicated on the visualization regardless of their true answer. The distribution of “answer truthfully”, “answer Yes”, and “answer No” on the wheel can be adjusted to tune the privacy protection in relation to the DP parameter $\epsilon$. Based on this procedure, the researchers found that participants were able to correctly identify the setting with the least risk to their privacy from several choices. These results suggest that providing individuals with an intuition on privacy risks is possible and beneficial for the individual’s decision-making. However, this positive result has two caveats. Firstly, we focus our research on the more common situation, where individuals have to decide whether a single presented privacy protection mechanism is strong enough for them to share their data. The results of Bullek et al. only measured the ability to select the most private option between multiple DP implementations offered and do not discuss how to support an absolute judgement. Secondly, they noted themselves that their explanations have the disadvantage that individuals perceived the mechanism used as lying when prompted to simply answer “Yes” or “No.” This prompted individuals in the study to act against their privacy preference to avoid having to lie by choosing the least private option.

Xiong et al. [65] investigated the comprehension of DP with different variations of real-world descriptions. They examined, for example, whether certain descriptions of DP are easier to understand or whether a positive framing of DP, i.e., its privacy guarantee, leads to different results compared to a negative framing of DP, i.e., the privacy risk. The researchers recognized that several unintentional differences in descriptions (e.g., the mention of a known institution that collects the individual’s data) had a stronger influence on individual’s decision-making than the influence of the differences in description.

Cummings et al. [19] also investigated various real-world descriptions of DP. They focused on the question whether a given description influences the privacy concerns and increases individuals’ willingness to share their data. They collected a set of 76 descriptions of DP and classified them into different themes (e.g., techniques, trust or risk). The effectiveness of a representative description for each theme was then compared to a control group with no description. They did not find any significant effects on the decision-making, postulating that none of the descriptions provided a meaningful enough mental model of DP. Nonetheless, they identified the descriptions that centered around privacy risk as the most promising, because this description conveyed the most accurate privacy expectations to individuals.

In summary, the existing research on how to explain DP to laypeople supports our hypothesis that communicating DP is challenging. Even developers and technically skilled people face the challenge of understanding DP in all its details [24, 30].

However, we hypothesize that individuals do not need an understanding of how the DP mechanism works in order to support informed consent. Instead, we should focus on explaining DP related to the impact on the individual, i.e., the possible privacy risk, building on Cummings et al. [19]. While communicating risk has been little explored in privacy research, risk communication in the medical domain is a well-developed field of research. In the following, we provide an overview of existing risk communication formats.

### 2.3 Risk Communication Formats

The goal of medical risk communication is to enable the patient, i.e., an individual, to make an informed decision about a particular treatment. Empirical results indicate that risk communication is by no means a one-size-fits-all solution. Instead, the effectiveness of risk communication depends on a variety of factors, for example, the range of the risk presented and the numeracy of the readers.
There are a number of meta-studies that offer recommendations on how to communicate risk effectively which allowed us to provide an overview of existing risk formats [10, 12, 27, 58, 59]. Based on these meta-studies, we decided to focus on communicating aleatory uncertainty, i.e., uncertainty about future outcomes, instead of epistemic uncertainty, i.e., uncertainty due to the lack of information. Furthermore, we do not consider 2-variate risk formats (e.g., natural frequencies) because they do not support our goal of explaining DP.

In the following, we briefly introduce six basic risk formats: percentages, simple frequency, fractions, numbers needed to treat, 1-in-x and odds. We provide a detailed overview of the risk formats identified in Appendix A. We also included two format variations that can be applied to the formats mentioned previously: outcome framing and comparison (i.e., comparison to known risks, comparison to peers and comparison to status quo).

A widely used format for risk communication is the relative quantification in percentages (e.g., “With this treatment, 23.8 % of patients experience dizziness”) [9, 12, 58]. Travena et al. [58] recommend this format especially when comparing multiple risks. McDowell et al. [38] suggest avoiding decimal points and presenting risks lower than 1 % as “< 1 %.” Simple frequencies are a slightly more general format [12, 27, 38, 58] (e.g., “13 out of 350 patients experience dizziness with this treatment”). This format presents the number (numerator) of cases affected by the event compared to a meaningful baseline (denominator), and is commonly accepted and understood by its readers. However, the choice of a meaningful denominator might affect the efficiency. Studies, among other things, strongly recommend using consistent denominators to compare multiple risks in the simple frequency format. Fractions are a useful format in verbal communication [10] (e.g., “Half of all people experience dizziness”). This format is used less for numeric communication as it is limited to a small number of commonly understood values and lacks accuracy. “Numbers needed to treat” statements is a format specifically developed for use in the medical context [27, 58] (e.g., “If 230 patients use this treatment, we expect one life to be saved”). This format is discouraged by multiple studies (e.g., [53, 59]) even in the medical context because it is neither well understood nor popular with individuals. The use of the 1-in-X format [47] (e.g., “1 in 5 patients experiences dizziness, while 1 in 10 experiences headache”) is widely discouraged. This is mostly due to difficulties of readers to accurately compare two risks presented in such a format. However, even in cases where only one risk is presented, Sirota et al. [51] find that risks in 1-in-X formats are perceived as significantly higher than the actual risk. The format of odds [59] combines positive and negative outcomes into one numeric fraction. However, this format has not yet been well researched in the context of risk communication.

These six basic formats can be combined with one or multiple of the following comparison or outcome framing variations. Firstly, a valuable information for individual intuition about a certain risk is the comparison to the risk of a similar event [12, 27] (e.g., “The risk of side effects from radiography is 15 %, which is only slightly higher than the 13 % risk of similar side effects from other common radiation sources”). Secondly, the risk of an event can also be compared to the risk of the same event for peers [12] (e.g., “Treatment A has a 15 % risk of suffering a heart attack, which is twice as likely compared to the average US American”). Finally, the risk of an outcome with an action can also be compared against the risk of the outcome without the action, i.e., the status quo [27, 58]. This is often used to explain the reduction of risk due to a treatment (e.g., “Treatment A leads to a survival chance of 60 % compared to a survival chance of 40 % without the treatment”).

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4We used Google Scholar with search terms “health decisions risk best practices review” and “health probability presentation best practices,” restricted to review papers and the last 15 years and manually screened the first 200 papers each by relevance.
All comparison variations discussed rely on two principle ways of representing the difference: the absolute risk reduction and the relative risk reduction. The latter is commonly discouraged in most cases since it is often misunderstood by individuals [59].

Another common variation is the outcome framing. Research has shown that the perception of participants is influenced by how (positive or negative) the outcome is presented. An event could be presented, for example, as “5 % of participants have side effects” or with the counter event “95 % do not have side effects.” Several publications (e.g., [53, 54]) recommend presenting the probabilities of both events together as “5 % have side effects, 95 % do not” to avoid bias induced by the presentation chosen.

In summary, this overview shows that communicating risk is a very active research area in medicine, however, communicating risk can easily lead to misinformation. Furthermore, the success of an approach depends on certain context factors (e.g., numeracy of the individual). Some formats, such as fractions, numbers need to treat, 1-in-x and odds, are not as flexible in use, not well researched, or not beneficial for individuals, and are, thus, discouraged. Instead, research encourages the percentages format and simple frequencies format. Multiple studies, furthermore, recommend presenting risk in relation to a comparable risk (either status quo, peers or a similar event) and to state the probability of the positive and negative event explicitly. We build upon this research in the remainder of this document and discuss how it can be used in the field of communicating privacy risks.

3 COMMUNICATING PRIVACY RISKS WHEN USING DIFFERENTIAL PRIVACY

The goal of privacy risk communication is to enable laypeople to make an informed decision regarding their privacy choices. However, as discussed previously, difficulties in communicating risks and DP exist, which currently prevent individuals from truly understanding the risk of sharing data when using DP.

We hypothesize that informed consent can only be achieved when individuals understand the risk associated with their consent. In order to facilitate this understanding, our research is driven by the following research question: What risk communication formats best support laypeople’s understanding of the privacy guarantees provided by DP?

We need to address two requirements to tackle this research question. Firstly, we need to define suitable formats for risk communication. Here we choose to base our formats on already evaluated research from the medical domain. However, since the usable formats and best practices for risk communication depend heavily on the application context, there is no obvious best choice and we need to consider multiple promising formats which are suitable for the privacy domain. Secondly, we need to translate the abstract parameter $\epsilon$ into a more intuitive notion of risk. As discussed, the parameter $\epsilon$ defines the trade-off between the accuracy of the data and the privacy of the individuals and, therefore, represents the privacy guarantees. However, it does not obviously constitute a presentable risk by itself and, therefore, an understandable risk has to be computed from it. We discuss these requirements in more detail in the next two sections.

3.1 Selecting Possible Risk Communication Formats

Risk communication formats used in the medical domain are well suited to represent privacy risks, as the two risk forms and decision situations are similar to each other: similar to the privacy consent situation, patients have to decide whether to undergo a treatment which changes the probability of an adverse outcome. The change in probability of the adverse outcome is specified but remains uncertain. Furthermore, research has shown that the recommended risk communication formats are comprehensible by laypeople and, therefore, suitable for our research question.
We know from Section 2.3 that two formats are recommended as best practice formats in different medical contexts, the percentage format and simple frequency format. In the following, we discuss these formats as base formats in the privacy domain. In addition to these base formats, we also consider possible variations.

We avoid decimal point in percentage formats by rounding to the nearest whole number. Risks between 0 and 1% will be shown as < 1%, as suggested by literature. An example of presenting a privacy risk in this format is: “When using DP, your risk of being identified in the dataset is at most 52%.”

Multiple options exist for the numerator and the denominator to represent the same risk in the simple frequencies format. There are multiple complementary best practices on how to make an appropriate choice, which also translate to the privacy domain. It is most important to choose a consistent number. For the denominator to minimize the mental load on the individuals when comparing different risks in this format. Small denominators are recommended because they are better understood intuitively and easier to remember by individuals. In addition, multiples or even powers of 10 as denominator have been shown to be beneficial [14]. We use multiples of 10 over powers of 10 in our representations to avoid unnecessary high denominators or inaccuracy due to rounding. Concerning the numerator, the use of 1 is discouraged, as it skews the risk perception of individuals. We prioritize avoiding 1 as numerator over the recommendation for small denominators due to the strong evidence for this effect [51]. An example that applies these considerations in the privacy domain is “When using DP, at most, 26 out of 50 participants are identified in the dataset.”

Another recommendation for both formats, percentage and frequencies, in the medical domain is the mention of a time frame, for which the risk presented is computed. There is no need to present a time frame with the risk since DP considers all information to be known from the date of publication. The individual is either identifiable immediately or will remain anonymous. We, therefore, do not apply this recommendation.

In addition to our two base formats, we also consider common variations of these formats and evaluate their usefulness in the privacy domain. We identified the two variations outcome framing and comparison to status quo, since they relate well with the risk associated with the DP method.

In both base formats, percentage and simple frequency, we present the probability of the negative outcome, i.e., the risk of being identified. The variation comparison to status quo adds to the respective base format the ground-probability of the same negative outcome - i.e., being identified - without the risk provoking event - i.e., being included in the data set. This variation is naturally related to DP, since DP compares by definition the probabilities in the two described situations. However, the other two comparison variations cannot be translated easily to the privacy domain. The concept of risk of an average person, as used in the variation comparison to peers, is difficult to translate into the privacy domain, as according to Bhatia et al., [11] privacy risk is highly subjective and can only be measured by unacceptably sever surveillance. Furthermore, for the variation comparison to similar event, the outcome of a possible privacy leak cannot be easily compared to any other well-known risky event because the data for such a comparison are not available.

In a second variation, outcome framing, we additionally present a counter-probability, i.e., that the same event does not occur. Thus, this variation describes not only the risk of an individual being identified but also the guaranteed probability of remaining unidentifiable. This variation is especially well suited, in the context of DP, since the mathematical definition of DP is formulated in terms of a privacy guarantee rather than a risk.

In summary, we selected two base formats: the percentage format and the simple frequency format. We added two variations for each base format: comparison to status quo and outcome framing. Thus, we arrive at six possible formats for communicating the privacy risks: \{percent, frequency\} × \{no variation, comparison to status quo, output framing\}.
However, we need to translate the parameter $\varepsilon$ into a risk we can represent in the formats identified to meet our goal of a risk communication that is based on a realistic setting. We discuss a possible approach for such a translation in the next paragraph.

### 3.2 Representing the Risk of DP

In the context of our research, we need to translate $\varepsilon$ into a probability of being identified. While a lot of work has addressed the mathematical mechanisms of DP, there has been little research done on how to interpret $\varepsilon$ as a risk [30, 35, 39, 42].

One possible approach for such a translation is provided by the model of Lee and Clifton [35]. They rephrase $\varepsilon$ as a probability of identifying any particular individual as being in the database depending on the number of individuals in the data set and the maximal impact of one individual on the outcome of the query. The disadvantage of this approach is that it requires additional parameters such as the number of individuals and the sensitivity (i.e., the maximum influence one individual could theoretically have on the outcome), which is often not available at the time of data collection.

Mehner et al. [39] simplified the model by Lee and Clifton, which we will use for our study. The model by Mehner et al. considers a worst case bound for the additional parameters. Thus, their model provides a translation of $\varepsilon$ into the desired percentage or frequency independent of any other parameters with the notion of global privacy risk $P$:

$$ P = \frac{1}{1 + e^{-\varepsilon}}. $$

Exemplarily, considering a value of $\varepsilon = 0.1$, we can easily calculate a global privacy risk of $P = 0.525$, which results in a probability of being identified as a percentage “52 %” or as a frequency “26 out of 50.” These values also directly determine the counter-probability of not being identified, as used in the variation outcome framing.

The format variation comparison to status quo requires the risk before sharing any data as a comparison. To this end, we use the worst-case value $P_{\text{guess}} = 0.5$ as outlined by Mehner et al. This value describes the probability of correctly guessing the presence of an individual in the data set without information from the data set, which corresponds to the status quo, before sharing one’s data. Obviously, we are able to present this probability as a percentage “50 %” and a frequency “25 out of 50”.

### 4 EXPERIMENTAL STUDY

Having identified the suitable risk communication formats, we designed and conducted an experimental study on Amazon Mechanical Turk (MTurk) in order to evaluate the suitability of our approach and differences in understandability between the formats selected. We performed a between-subject study to avoid potential learning effects.
4.1 Study Design

Our study setup was divided into six phases: The participants (1) were introduced to a scenario with a focus on mobility data; (2) were shown one of seven conditions at random, i.e., privacy notifications (six risk communication formats as discussed in Section 3.1 and as baseline condition “DP Imp. (22)” from [65]); (2a) were asked to self-rate their understanding of the notification to derive their subjective understanding; (2b) were asked to answer objective (true or false) questions about the privacy risks of DP; (3) completed standard tests about their privacy aptitude and their statistical numeracy, and, finally, (4) were asked to indicate their perceived gender. We describe the design consideration for each phase in the remainder of this section (cf. Figure 3).

We defined a fictional scenario to capture the complexity of privacy risks that focuses on the collection of mobility data from users of a ridesharing service and app. We decided to focus on ridesharing services due to their increasing popularity. Hence, the scenario illustrated has a high likelihood of being relatable for the participants in our study. The quality of the scenario was evaluated in a thinking-out-loud session with English native speakers before the start of the study.

The scenario describes that, after an app update, user data from the ridesharing app will now be shared with a local authority to improve the urban infrastructure. As part of the scenario, the user receives a notification, explaining the use of DP and the potential privacy risks. The text of the notifications shown differed according to the condition selected for the participant. We adapted the description “DP Imp. (22)” from Xiong et al. [65] as baseline condition as it was the best performing description of DP in their study.

Additionally, we specified six notifications, based on the six risk communication formats identified in the literature study (cf. Section 3: two base formats frequencies and percentages, each in their basic form and with either of the two variations, comparison to status-quo and output framing).

Each text included in these notifications starts with the first sentence of the baseline condition, to convey the basic information about DP in a comparable way. It is then followed by the corresponding risk communication format based on similar risk communications in the medical context compiled by Bansback et al. [10]. The wording used in the six descriptions was developed in multiple iterations with experts on DP and DP laypeople. We aimed for the technical/mathematical correctness of DP and simultaneously an understandable description for general users. All conditions used in our study can be found in Table B.4.

We also used a rather strong value for the DP parameter $\varepsilon = 0.1$ as the wording of the baseline condition suggests strong privacy guarantees. With this parameter, we derived the risk values for the risk communication formats using the model by Mehner et al. [39]. Thus, all risks presented are actually representative of the DP parameter chosen.

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$^5$The complete scenario can be found in Appendix B.2.
Finally, we presented the text of the notifications in a depiction showing a stylized smartphone with a suggested ridesharing app in the background and a typical design of a notification in the foreground to support immersion of the participants in the scenario. An example for the notification is provided in Figure 7.

After exposing the study participants to our descriptions, we evaluated their subjective and objective understanding of the outcome of the DP mechanism described (cf. Appendix B.3). We asked participants to rate three statements on a 7-point Likert scale for the evaluation of the subjective understanding. These statements asked directly for their perceived general understanding, their perceived ability to assess individual privacy risks based on the description and whether the descriptions lacked any necessary information.

Concerning the objective understanding, we intended to establish how effectively the descriptions enabled participants to classify the privacy risk with similar and common techniques. We compared the privacy risk of DP with the risk when sharing the unprotected data and when sharing no data at all. In addition, we asked about two basic principles of DP. Where possible, we randomized the correct answer (true/false) of these questions by varying the qualifier (less/more, higher/lower).

In addition to our research question of how risk formats perform in the context of individual privacy, we considered a number of context factors of risk communication. An important influence for the effectiveness of risk communication is the statistic numeracy, i.e., how experienced participants are in dealing with statistics in general. We include the Berlin Numeracy Test [17] in its adaptive format to measure the influence of statistic numeracy on the effectiveness of our descriptions. Research also shows an influence of gender, especially on the perception of positive or negative framing of risk communication [31]. We, therefore, ask participants to reveal their gender and for this, we followed the recommendations by Spiel et al. [55]. Finally, in the area of privacy risk communication, privacy aptitude is an obvious potential influence. We adapted the Internet Users’ Information Privacy Concerns test (IUIPC) by Malhotra et al. [36] to evaluate the privacy aptitude of participants. This test divides the privacy aptitude into the three dimensions “control,” “awareness,” and “collection,” each with three to four questions. Since our goal is to investigate the understanding of privacy risks rather than the influence on sharing decisions, we excluded the test’s “control” dimension. We measured instead only for “awareness” and “collection,” which are both directly relevant to our scenario.

We included comprehension check questions after the scenario and attention check questions as part of the objective understanding, and the privacy aptitude test to exclude inattentive participants. At the beginning of the study, we informed the participants that MTurk IDs and IP addresses would be stored for quality control purposes, but would be deleted once quality was verified. We also explained the collection of gender information to the participants and its purpose in the study. The complete introduction can be found in Appendix B.1.

In summary, for this study we consider the condition shown (i.e., privacy notifications concerning DP) as the independent variable, the subjective and objective understanding as dependent variables, and numeracy, privacy aptitude and gender as covariates.

### 4.2 Participant recruitment

Although MTurk has known disadvantages concerning nuanced representation of users [6], its advantage of reaching a wide audience in this early investigation into the suitability of the risk communication formats outweighs this concern.

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6 How important is control of personal data and autonomy?

7 How important is the knowledge concerning how personal data is collected, processed and used?

8 How concerned is the participant with data collection?
We restricted participants to MTurk workers with at least 95% approval rating and at least 1,000 approved assignments. As customary, we restricted participants to join exclusively from the US, to increase the likelihood of an adequate English proficiency. We determined a working time of about 12 minutes, with careful reading of all material, in a small pre-test run with a few selected participants (recruited from our research group as well as project partners). Conservatively we based the compensation on a working time of 15 minutes. Consequently, each participant was paid $3.00 ($12.00/hour), which is significantly higher than the local minimum wage (~$10.01/hour at the time of recruitment) and about equal to the average hourly wage on MTurk (~$12.05/hour). However, we allowed up to 40 minutes per participant to avoid automatic timeouts of participants who were slower for any reason. The MTurk assignments were distributed throughout the day between reasonable US working hours.

4.3 Sample size and attributes
Based upon an *a priori* power analysis, we aimed for a sample size of 338 submissions and collected a total of 444 submissions. However, 101 submissions were excluded for failing attention or comprehension check questions (95), and due to repeated participation (6). Consequently, the study included 343 submissions.

Of these of 343 participants, 223 considered themselves to be male (with 65.0% slightly higher than comparative studies [37]) and 117 as female; 3 participants reported being non-binary or self-described.

The results of the test on statistical numeracy were highly skewed towards low numeracy. A total of 175 participants scored in the lowest group, 47 participants are grouped in "rather low," 39 as "rather high" and 82 in the highest group. According to the authors of the test [17], we expected, instead, four equal groups. The test, however, was validated with university-affiliated participants. In MTurk studies [41], only around 49.46% of workers report holding a bachelor’s degree or higher with no data on how long the degree dates back. The high ration of participants without university experience plausibly explains the difference to the evaluation study.

5 RESULTS
In this section, we present the procedure and the results of our statistical analyses. We start with investigating the direct effect of the risk formats on participants’ understanding (cf. Section 5.1) and, then, present findings about the influence of the additionally collected individuals’ characteristics on the risk formats' effectiveness (cf. Section 5.3). In our analyses, we use a significance-level of $\sigma = 0.05$ and adjust the pairwise t-tests with Bonferroni-corrections.

5.1 The Effect of Different Risk Formats on Subjective and Objective Understanding
First, we investigate the influence of the shown conditions (e.g., *FreqPure*) on subjective and objective understanding. As described in Section 3, the *subjective understanding* consists of three questions on a 7 point Likert-scale. For each participant, we calculated the value for subjective understanding as the arithmetic mean of the three answers. A high value of subjective understanding denotes that the participant felt confident in their understanding. While testing the preconditions on an ANOVA test for correlation, we discovered that the variances of the subjective understanding were too dissimilar between the conditions (Levene test $p = 0.04663$). We opted for a Welch-ANOVA.

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9[http://faircrowd.work/platform/amazon-mechanical-turk/#platform-information](http://faircrowd.work/platform/amazon-mechanical-turk/#platform-information), accessed 10.12.2021
10We provide all anonymized data and our R scripts under open access on OSF upon acceptance of the article.
11Pairwise t-tests compute many correlations on the same data set. By the nature of these correlations, the likelihood of discovering false correlations increases with the number of computed correlation values. Bonferroni is one of the common practises to correct the resulting values for this effect.
Franzen et al.

(a) Mean subjective and objective understanding of participants in each condition.

|               | Subjective Understanding | Objective Understanding |
|---------------|--------------------------|-------------------------|
| FreqPure      | 4.88                     | 1.69                    |
| FreqPosNeg    | 5.05                     | 1.63                    |
| FreqStatQuo   | 4.58                     | 1.98                    |
| PercPure      | 5.07                     | 1.61                    |
| PercPosNeg    | 5.11                     | 1.88                    |
| PercStatQuo   | 4.99                     | 1.58                    |
| BaseLine      | 5.60                     | 1.79                    |

(b) Pairwise t-test (Subj. Understanding)

|                | (1) | (2) | (3) | (4) | (5) | (6) |
|----------------|-----|-----|-----|-----|-----|-----|
| FreqPure       | -   | -   | -   | -   | -   | -   |
| FreqPosNeg     | 1.00| -   | -   | -   | -   | -   |
| FreqStatQuo    | 1.00| 1.00| -   | -   | -   | -   |
| PercPure       | 1.00| 1.00| 1.00| -   | -   | -   |
| PercPosNeg     | 1.00| 1.00| 1.00| 1.00| -   | -   |
| PercStatQuo    | 1.00| 1.00| 1.00| 1.00| 1.00| -   |
| BaseLine       | 0.28| 0.80| 0.0074|∗∗ | 1.00| 1.00| 0.70|

5.2 Preprocessing of Individual Characteristics

In addition to subjective and objective understanding, we collected data on participants’ characteristics, i.e., numeracy, privacy aptitude, and gender. To prepare further analysis, we present in this section the processing steps we used for this data and the considerations regarding the preconditions for the analysis methods used in the following section.

We divided the numeracy of the participants, according to the used numeracy test\(^\text{12}\), into four levels: lowest (\(\text{lowestN}\)), low (\(\text{lowN}\)), high (\(\text{highN}\)), and highest (\(\text{highestN}\)).

We used the results from the privacy aptitude questionnaire, to compute separate arithmetic means of the answers for the dimensions “awareness” (three questions) and “collection” (four questions) for each participant. We then calculated the arithmetic mean of these two values to get an aggregated value for the privacy aptitude on a scale between 1 and 7.\(^\text{13}\)

Lastly, we considered participant’s self-assigned gender. We excluded the non-binary gender-categories in the following tests involving gender, since the sample size was too low (three submissions).

\(^{12}\)As explained, we used the Berlin Numeracy Test (BNT) by Cokely et al. [17] that classifies each participant into one of four levels according to the correctly answered questions based on a flow-diagram.

\(^{13}\)For example, if a participant answered (5,3,7) on awareness and (3,6,2,5) on collection, we calculated awareness = \((5+3+7)/3 = 5\), collection = \((3+6+2+5)/4 = 4\), and finally privacyaptitude = \((5+4)/2 = 4.5\).
As preconditions for the following tests, we checked possible correlations between the conditions and the individuals’ characteristics, i.e., numeracy, privacy aptitude, and gender. Due to the rigorous rejection based on the attention check questions, we are confident, that we had removed most outliers caused by the survey design, already. Therefore, we preceded without the removal of outliers and were able to successfully reject any correlations between the characteristics (i.e., numeracy, privacy aptitude or gender) and the conditions.

Nevertheless, to increase the chances of finding stronger results about the general population, we considered outlier removal. Following existing guidelines\textsuperscript{14} we removed 14 outlier from the data set.\textsuperscript{15} After outlier removal, we discovered that a correlation between the conditions and the results from the privacy aptitude test could not be rejected (ANOVA with $p = 0.0184$). In order to investigate possible causes for this correlation, we performed a pairwise t-test using the privacy aptitude as the output variable, resulting in no significant effects of one single condition over another (cf. Table 2). An effect of the conditions on the results of the privacy aptitude test can, therefore, not be confirmed.\textsuperscript{16}

Consequently, we continued with the analysis including the 14 outliers. With the full data set, the mentioned correlation can be rejected (ANOVA with $p = 0.2563$).

As precondition for a linear regression model, we again considered privacy aptitude, since it is the only numerical value. We plotted the values for privacy aptitude against the subjective understanding (cf. Figure 4) and discovered, that the relation was not linear, with rising values in subjective understanding up to a privacy aptitude value of 5.3, a plateau up to around 6.2, and falling subjective understanding afterwards. As preparation for the linear regression model, we, therefore, categorized privacy aptitude according to these three different areas into three levels low ($lowP$), medium ($mediumP$), and high ($highP$) instead. This categorical representation will be used in place for the privacy aptitude in the linear regression model in the following section.

\textsuperscript{14}https://statistikguru.de/spss/einfaktorielle-anova/voraussetzungen-5.html
\textsuperscript{15}We defined responses as outliers if their value was more than 1.5 times of the interquartile range above or below the lower or upper quartile.
\textsuperscript{16}We discuss possible causes for this effect in Section 6.3.
5.3 The Effects of Individuals’ Characteristics

In Section 4 we hypothesized that numeracy, privacy aptitude or gender might have an influence on the effectiveness, i.e., the subjective and objective understanding of the risk communication formats.

To get an impression of the effects of these characteristics, we calculated a full ANOVA model with all main-effects and the interaction effects between the conditions and each characteristic. Due to the categorical values of the gender covariate, we did not include gender in this model, resulting in 5 predicates (condition, numeracy, privacy aptitude, interaction of condition with numeracy, interaction of condition with privacy aptitude). In the model for the subjective understanding, we find a significant effect only for the numeracy ($p = 0.0007152$). The correlation is negative, indicating that the subjective understanding decreases as numeracy increases.\(^{17}\) The equivalent ANOVA model for the objective understanding did not indicate any significant effects ($p \geq 0.1093$).

To evaluate our hypothesis, we constructed two regression models; the first model looks into the influence of the characteristics on subjective understanding, and the second model on objective understanding. We include seven predicates for each model: (1) condition, (2) numeracy, (3) privacy aptitude, (4) gender, and (5-7) three interactions between conditions and each of the characteristics.

As base categories for the linear model, we used the BaseLine condition, the highest numeracy level $\text{highestN}$, the medium privacy aptitude $\text{mediumP}$, and the gender $\text{male}$.\(^{18}\) Calculating this model for the subjective understanding, we observe significant effects for PercStatQuo ($p = 0.0255$)

\(^{17}\)We will discuss this effect further in Section 6.4.

\(^{18}\)These base categories define the group to which differences are calculated. We aim to discover differences caused by the risk communication formats. Thus, we choose the BaseLine condition for comparison. Since we expected higher differences in lower levels of numeracy, we selected the highest level of numeracy to discover differences to the lower levels. For privacy aptitude we did not have an intuition and, therefore, chose the medium level to discover effects of the levels low and high simultaneously. The choice for gender base category is irrelevant with only two considered values. We kept the value $\text{male}$ for gender as chosen be the linear regression model.
“Am I Private and If So, How Many?”

Fig. 5. Effect of Numeracy on Subjective Understanding

and for the interaction between the condition PercStatQuo and numeracy lowN ($p = 0.0248$). The table of all regression coefficients is shown in Appendix C.1.

In Figure 5, we show the subjective understanding per condition separated into four numeracy levels. For example, “lowestN.FreqPure” denotes the subjective understanding for the numeracy level lowestN of all participants in the FreqPure condition. The diagram reveals that the PercStatQuo condition has one of the lowest results in the sub-groups lowestN, highN and highestN (cf. “lowestN.PercStatQuo”, “highN.PercStatQuo”, “highestN.PercStatQuo”). The subjective understanding of participants in the PercStatQuo condition with numeracy lowN, i.e., “lowN.PercStatQuo”, however, has a higher medium performance than in any other condition.

Furthermore, the four numeracy groups of the PercStatQuo condition show a distinct pattern of subjective understanding; the subjective understanding is moderate in the lowest numeracy level lowestN, then it continues with a higher value in the low numeracy level lowN, followed by a low value for the high numeracy level highN, and finally again with a moderate value in the highest numeracy level highestN. This pattern can also be seen in the BaseLine, PercStatQuo and PercPure conditions, though the effect in these conditions is not significant.

We defined an equivalent linear regression model for objective understanding (cf. Appendix C.2) which returns a significant effect ($p = 0.033435$) only for participants with low privacy aptitude lowP in the FreqPure condition. In Figure 6 a boxplot shows that these participants performed worst in objective understanding. However, this is an isolated finding which cannot be observed in any other group.
DISCUSSION

The overarching goal of our research is to enable laypeople to share their data for the benefit of the public in a privacy-concerning manner by employing a privacy-preserving computation technique. This aim requires two things: firstly, we need to utilize a privacy-preserving technique, here, DP, and secondly, individuals need to understand the consequences, i.e., the remaining privacy risks, when sharing their data. When asking people to share their data anonymously by employing a DP mechanism — a technique that has shown to be hard to understand — we propose using risk communication formats. In our study, we compared risk communication formats informed by related research in the medical domain to existing best practice and investigated the understandability of these formats, i.e., subjective and objective understanding. In the following section, we, firstly reflect on the results of our study and in the subsequent section, we discuss how these results might inform future research activities.

We discuss our results from four angles. Firstly, we highlight the general suitability of using risk communication formats for DP. Secondly, we reflect on how the risk communication formats influence subjective and objective understanding, and thirdly, we speculate about possible reasons for the correlation between conditions and privacy aptitude. Finally, we discuss how numeracy influences the understandability of risk communication formats.

6.1 Suitability of Risk Communication Format

We used existing research from the medical domain (cf. Section 2) to design six risk communication formats that include realistic quantitative information, i.e., mathematically rigorous worst-case estimates (cf. Section 3.2), about the likelihood that certain sensitive data are revealed to unauthorized parties. By building on existing research from usable security and privacy (cf. [19, 65]), we extended the existing qualitative risk communication formats by adding this quantitative information as textual descriptions and showed them transparently to users.
Our study results provide first evidence that the inclusion of numbers describing an existing risk quantitatively does not significantly harm the objective understanding and, thus, the informed decision-making of the participants. Instead, the risk formats perform similar to and, in some cases, slightly better (yet not significantly) than existing best practice by Xiong et al. [65]. This is an important result, because it encourages further research into the use of privacy risk communication formats to transparently inform individuals about possible risks when sharing their data.

Our results also support the insights by Bullek et al. [15], who highlight the usefulness of transparency when using DP mechanisms for understandability. Such understandability (e.g., [2, 4]) allows for two future or potential modes of use of DP. On the one hand, individuals can add “noise,” i.e., select a certain $\epsilon$, themselves (local DP) or, on the other hand, this decision is entrusted to an authority (global DP).

### 6.2 The Influence on Subjective and Objective Understanding

The results regarding the overall effect of the conditions on subjective understanding show that the BaseLine condition outperforms all risk communication formats in the basic mean value, and even significantly outperforms the condition FreqStatQuo. However, the results regarding objective understanding show a different behaviour: two of the risk communication formats, i.e., FreqStatQuo and PercPosNeg, outperform the BaseLine condition according to the basic mean value. All other risk communication formats perform less well in terms of mean value, but no significant difference could be found. We want to stress that the questions concerning the objective understanding did not relate to the additional quantitative information contained in the risk representations. Our questions focused only on the basic properties of DP, which were also included in the BaseLine conditions. Consequently, we assume that all conditions had indeed similar effects on objective understanding.

However, the results regarding objective understanding were generally surprisingly low concerning all conditions: with four true/false questions by random chance one would expect two correct answers. The overall arithmetic mean score on objective understanding in our sample set was 1.74 with only condition FreqPosNeg achieving a result close to random expectation with an arithmetic mean of 1.98 (cf. Table 1a).

This suggests that the level of information provided in our risk communication formats and the BaseLine condition is insufficient for understanding the properties of DP. We discuss this aspect in more detail in future research (cf. Section 7.2).

The two results on objective and subjective understanding seem to be contrary to each other. The risk communication formats perform similarly to the BaseLine format on objective understanding, but less well on subjective understanding. This difference is especially pronounced regarding the condition FreqStatQuo, which performs significantly lower than BaseLine on subjective understanding, yet, achieves the highest overall value for objective understanding. One possible explanation for this different behaviour is that the BaseLine condition creates a feeling of confidence, while the risk formats cause a more cautious reaction. However, this feeling of confidence caused by the BaseLine condition (5.6 mean out of possible 7) is not backed up by the objective understanding measured, as discussed above. Thus, participants become too confident concerning their level of understanding in the BaseLine condition.

This effect might lead to an undesirable situation, where data owners are incentivized to optimize privacy notifications to maximize the feeling of confidence regardless of the actual objective understanding. This undesirable situation has been researched in various settings, for example, under the term dark patterns (e.g., [52]). Similar to research by Sirota et al. [51], we should instead determine for which communication formats the subjective understanding corresponds best with
the objective understanding. Such a format would support informed consent, as it enables individuals to know when to seek more information.

Finally, we want to remark that the quantitative information contained in our risk communication formats might have additional benefits in judging the magnitude of the privacy risk. As noted above, the questions for objective understanding used in our study did not capture this information for comparability with the BaseLine condition. Future research will have to evaluate whether this can further increase the objective understanding of the risk described. The framework presented by Bhatia et al. [11] could be a promising starting point for measuring the correct perception of risk provided by the different risk communication formats.

6.3 The Effect of Individual’s Privacy Aptitude

Our results suggest a correlation between privacy aptitude and the conditions. Since we assigned participants randomly to each condition, there should not be an effect of the group on the privacy aptitude by design; however, a correlation between the two could not be rejected. We provide two possible reasons for this relationship.

Firstly, throughout our study, we provided participants with the option to quit and delete all answers recorded at any point in the study. Different levels of privacy aptitude might prompt participants to use this option in different circumstances: Participants with high privacy aptitude, for example, might have quit more often when seeing one condition and participants with lower privacy aptitude might have quit more often when seeing another condition. Unfortunately we cannot confirm this because we removed all records of the aborted study sessions. Secondly, another possible explanation for the relationship is the order of questions in our questionnaire: we did not randomize the order of the parts of the survey for technical and operational reasons. All participants answered the privacy aptitude questions after reading the conditions. Due to this order, it is possible that the conditions temporarily influenced the participants to answer differently in our privacy aptitude test.

This observation might relate to the well-known privacy paradox [3], which describes the difference between the privacy behaviour of individuals and their privacy aptitude measured separately. In our study, having read the privacy notifications, the participants answers in the Internet Users’ Information Privacy Concerns questionnaire might not reflect their actual privacy aptitude, but instead were influenced by the condition. In the worst case, this effect could further increase the privacy paradox, when notifications intentionally or unintentionally manipulate the participants behaviour further away from their actual privacy aptitude. Alternatively, this effect could be used for the benefit of the individual. The effect could be reduced by choosing notification formats which act in opposition to the privacy paradox. Similar work has been done under the name of nudges (e.g., [25]). Since we could neither reject nor confirm the effect between the condition and the privacy aptitude in our study, further research is needed to investigate this relationship.

Concerning objective understanding, we found that participants with low privacy aptitude performed less well with the condition FreqPure. Since this is an isolated finding we cannot speculate about the reason for this performance. If this effect can be confirmed in future studies, the use of frequencies format in privacy notification without additional information could not be recommended.

6.4 The Effect of Numeracy

In Section 5.3, we have seen a negative effect of numeracy on subjective understanding, which is further characterized by the pattern discovered (cf. Figure 5) for condition PercStatQuo, and less pronounced with conditions FreqStatQuo, PercPure and BaseLine. Thus, this effect seems to be dominantly present in percentage formats and in the status quo formats. This would explain the
significance for the PercStatQuo condition, as this condition combines both properties – percentages with the status quo variation.

Furthermore, the shape of the pattern (cf. Figure 5) resembles the Dunning-Kruger effect [33]: when educating a low educated individual, the confidence first rises overproportionally to the new knowledge acquired, before suddenly dropping sharply. The confidence rises again to an appropriate level only after reaching an expert level of education. The same shape can be seen in our data. The Dunning-Kruger effect sounds especially plausible, as it only applies to the confidence, i.e., subjective understanding, not to the actual knowledge, i.e., objective understanding, parallel to our discovered results.

This distribution of subjective understanding to numeracy contributes to increase the “technocracy” discussed by Agrawal et al. [5]. Individuals with the lowest and low numeracy are confident of having understood the notification without grasping all the potentially severe consequences to their privacy. This overconfidence could lead to them agreeing more often to sharing data and, therefore, being more vulnerable.

Alternatively, to decrease the consequences of the “technocracy,” this result opens up the possibility for personalized privacy notifications in the form of an adaptive user interface: if the approximate numeracy of an individual is known, the notification could be tailored to the numeracy of the individual, for example, cautioning individuals with lower numeracy while affirming individuals with higher numeracy, in sum, balancing the different effects on subjective understanding. The level of numeracy of an individual can, for example, be captured by a short questionnaire before the actual sharing decision. This is especially applicable in more complex sharing decision, such as in the medical domain.

In situations where such an adaptive user interface is not feasible, we suggest the use of descriptions, such as FreqPosNeg, which, based on our results, does not discriminate against different numeracy levels.

7 LIMITATIONS AND FUTURE WORK ON RISK COMMUNICATION FORMATS

This study provides novel insights into using quantitative risk communication formats to inform laypeople about privacy risks when sharing their data. However, our study has a number of limitations; at the same time, our results are hypothesis-generating and open up a number of promising research directions that may help to shape the way in which we enable people to share their data securely and in a private manner. We next discuss both limitations and future research.

7.1 Situating Risk Communication in the Real-World Context

MTurk enabled us to quickly recruit a large sample within the budgetary requirements. However, we are aware of existing caveats caused by such a study design, especially regarding ethical and quality assurance concerns, and concerns regarding the appropriateness of its users.

First of all, we considered existing recommendations for using MTurk (e.g., [48, 57]) and guidelines, for example, given by Fair Crowd Work\(^\text{19}\). We informed, for example, all participants of any personal data collected before they accepted the task, provided means of aborting and deleting the collected data throughout the task, and handled the results anonymously where possible.

Secondly, using crowd workers as our participants, we have to consider MTurk’s incentive structure: MTurk awards fixed payments per task. This encourages spending as little time as possible on reading the study texts and thinking through all possible repercussions of a decision (cf. [22]). We employed comprehension and attention checks to minimize the effect of this disadvantage and to ensure results comparable to conventional participation recruitment procedures (cf. [6]).

\(^{19}\text{For further information please check http://faircrowd.work/platform/amazon-mechanical-turk/#platform-information.}\)
Finally, we discussed the appropriateness of MTurk users for our research question. Recent surveys (e.g., [56]) revealed that MTurk Workers are reasonably representative of the general population in the US (population validity). Thus, based on our MTurk study, we get a better understanding of the design space of risk communication formats when employing DP. However, transferring these insights into other cultural settings (e.g., the European context) requires additional validation.

Furthermore, participants can only imagine the scenario provided, where privacy might be threatened. Behaviors and considerations are highly situated and might differ when participants contribute their real personal data. The external validity of our research is low, therefore, we will conduct participatory design workshops (e.g., [13, 61]) with citizens in the context of urban mobility. We will work closely with an institute for transport research that collects mobility data via smartphones to achieve this. Such participatory design workshops will allow us to extend the variables considered, for example, how these descriptions relate to users’ concrete sharing decisions, similar to work by Wu et al. [63].

7.2 Exploring Alternative Risk Communication Formats

Our findings show that quantitative risk communication formats perform comparably to a description that explains DP without quantitative information (Baseline condition derived from Xiong et al. [65]) in objective understanding. However, as noted before, the overall results in objective understanding were very low, which indicates general difficulties understanding the properties of DP. We defined our quantitative risk descriptions with approximately the same length as the Baseline DP description to ensure comparability. In future work, alternative risk communication formats (in terms of their length or their visual representation) might help to increase both the objective and subjective understanding of individuals and even avoid the possibly existing overconfidence effect of the DP descriptions. There has already been promising research done on visual aids in the medical domain and, concerning privacy, Xiong et al. [65] investigated the effect of a "Fact Box"20 to explain DP. However, the results of their study are not yet available.

We use our mathematically rigorous worst-case estimate (cf. Section 3.2) regarding the likelihood that certain sensitive data are revealed to unauthorized parties. However, we limited our privacy notifications to one value for $\varepsilon$ only, as this is the default situation in current privacy decision settings. Future work could offer multiple values for $\varepsilon$ within the privacy decision setting. Bullek et al. [15] have already provided promising results for such a setting. They showed that explanations of DP can convey the relationship between the privacy protections of several DP options, however, their explanations do not convey the absolute privacy risks of each option. Explanations that can achieve both goals, i.e., conveying the relation between different options and the absolute privacy protection of each option, would enable laypeople to select the most appropriate $\varepsilon$ value according to their personal privacy preferences in a specific situation. Such a scenario could benefit from additional results in the medical domain, where the risks of different drugs often have to be compared to each other. We discovered in our literature review (cf. Section 2.3) that certain risk communication formats are preferable in single risk communication, but others are recommended for comparing multiple risks. We, therefore, expect that the results of this study are not easily transferable to a setting when choosing between multiple $\varepsilon$ values. Future work is necessary for evaluating the benefits of such approaches.

Finally, our findings suggest that privacy aptitude and the numeracy influence the effectiveness of the risk communication formats in certain situations. A possible direction for future research

20 A "Fact Box" is a visualization or tabular summary of data often used in a medical context to show dependencies (e.g., of a particular disease and treatment) between one’s position relative to others affected in the same situation (e.g., [14]).
might be to design adaptive user interfaces that tailor privacy notices according to the individual’s characteristics and, thus, enhance the understandability of the privacy notice. Such research can build on existing research in the area of explanations (e.g., [40]). However, the need for better explanations has already been highlighted within an interview study by Agrawal et al. [5], in which the participants suggested that explanations should be even part of a standardization process and included within software libraries. Such a standardization process is not restricted to the technical domain but might impact policy making as well, which we discuss next.

7.3 Towards Contextual Anonymity

Our research is driven by the vision to enable people to make an informed decision when sharing their data. An informed layperson should understand the consequences of sharing personal data. Thus, we used results from risk communications in our interdisciplinary project together with a mathematically rigorous model of DP for the translation from the parameter $\varepsilon$ into one numeric risk value (cf. Section 3.2). The major advantage of this approach is that the privacy notification we displayed shows accurate information as it could appear in a real-world setting rather than made-up unrealistic risk values. However, by applying the interpretative privacy risk model of Mehner et al. [39], we rely on a worst-case estimate to derive a risk value, independent of factors such as sample size or sensitivity of a query. Future work should, in addition, consider other models, which compute the risk value based on different assumptions and parameters, such as of Naldi and D’Acquisto [42] or Hsu et al. [30], and examining them for comprehensibility as well.

Furthermore, we hope that our research might provide the basis for making DP understandable and applicable to a broader range of people for making the abstract disadvantage of sharing the data, i.e., the risk, tangible. Current research focuses on showing which data is being exchanged for what purposes, for example, based on icons (e.g., [18]), or visualizations (e.g., [29]). This research assumes that people are sharing their data, but what they are sharing is the risk of someone unauthorized accessing their personal information. We hope we can inform discussions in the policy domain by translating the abstract, intangible concept of “data sharing” into something more concrete. We envision the use of DP as a tool for contextual anonymity that can be realized in two directions. Firstly, instead of communicating the purpose of data sharing, such as required by the General Data Protection Regulation, protection measures should be defined for specific areas of applications (e.g., for medical data). When applying DP, such protection measures define an upper bound for $\varepsilon$ (cf. Section 2.1). Secondly, based on such legally defined protection measures, laypeople can decide based on a risk communication format whether, in a concrete situation, the privacy protection proposed is sufficient for them and if not, lower the value of $\varepsilon$ to increase noise and, consequently, to increase their protection.

8 CONCLUSION

The undesirable use of personal data by companies and governmental agencies has created a growing unease in people’s perception regarding the necessity of sharing data. This unease impacts especially legitimate uses of data donations, for example, for the sustainable development of urban infrastructures. People are increasingly less willing to share their personal data because they have privacy concerns. A major challenge is, therefore, to collect data by preserving people’s privacy. A possible approach would be to anonymize the data. However, conventional techniques, such as simply removing identifying information, are insufficient, as sensitive information can often be rediscovered by the use of externally available information [43]. A more recent technique to balance the need for accuracy while preserving privacy is Differential Privacy. However, research has shown (e.g., [5]) that communication methods are needed to support individuals in understanding how such techniques can protect their privacy. Our research takes the first step in this direction by
suggesting the use of risk communication formats that are informed by research from the medical domain. We combined these risk communication formats with a mathematically rigorous DP model, which translates the unintuitive DP parameter $\epsilon$ into an understandable risk value. With this combination, we achieve accurate notifications that explain the privacy risk of data sharing when DP is used for anonymization. These new communication formats, thus, do not only inform about the use of DP, but also communicate the impact DP has on the privacy of the individual.

We evaluated the understandability of our proposed communication formats in a crowdsourced experimental study against a well-performing description of DP (baseline) and found that our formats perform similarly in objective understanding, which makes the risk communication formats a promising research area. In subjective understanding, however, the risk communication formats lag behind the best practice baseline condition. Future research will have to show whether additional existing results and communication tools, such as visual aids, can negate this lack of confidence and increase the overall subjective and objective understandability. Furthermore, we discovered that numeracy and, in some cases, privacy aptitude influences the subjective understanding of multiple different formats, including the best practice DP format used for comparison.

We hope that we can gain a better understanding of these relationships in future studies to benefit people in two ways: firstly, we hope we can inform policy making for “data security by design” by making DP more assessable to laypeople (through the use of risk communication formats). We envision that an individual’s privacy is ensured by defining a upper bound of $\epsilon$ in specific data contexts, for example, medical data or trajectory data. Secondly, we anticipate that individuals will be able to contextualize their privacy preferences by adaptive privacy notifications. Such notifications should be tailored to an individual to achieve the best possible understandability when choosing $\epsilon$ for realizing an informed consent.

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Appendix

A RISK COMMUNICATION FORMATS

An overview of all formats with sources and pros and cons can be found in Table 3
| Format          | Description                                                                 | Examples                                                                 | Possible Variations                                                                 | Recommendations / Comments |
|-----------------|------------------------------------------------------------------------------|--------------------------------------------------------------------------|-------------------------------------------------------------------------------------|----------------------------|
| Percentage      | Relative frequency with baseline 100                                         | <1% of the participants are re-identified                                | • Describe pos. and neg. outcomes,                                                 | • Recommended for comparing multiple risks |
|                 |                                                                               |                                                                          | • Compare to Known Risk / Peers / status quo                                      | • Avoid decimal point → rounding |
|                 |                                                                               |                                                                          |                                                                                    | • 0% > p > 1% as < 1% |
|                 |                                                                               |                                                                          |                                                                                    | • Percentages better for comparing two events than frequencies |
| Simple          | Present the number of affected people in relation to meaningful baseline      | 3 out of 350 participants are re-identified                              | • Describe pos. and neg. outcomes,                                                 | • Denominators |
| Frequencies     |                                                                               |                                                                          | • Compare to known Risk / Peers / status quo                                      | – consistent |
|                 |                                                                               |                                                                          |                                                                                    | – as small as possible |
|                 |                                                                               |                                                                          |                                                                                    | – powers of 10 |
|                 |                                                                               |                                                                          |                                                                                    | • avoid 1 as numerator |
|                 |                                                                               |                                                                          |                                                                                    | • specify time frame |
| Fractions       | Present the fraction of affected people as textual representation             | Half of all statistics will reveal whether you visited a location        | Variations not feasible due to accuracy                                            | • Well understood, if representation is available |
| Numbers needed  | How many people need to do the action, before 1 is expected to be affected by | 117 Participants need to participate before we expect a participant to be   |                                                                                    | • discouraged by [53, 59] |
| to treat        | the risk                                                                      | re-identified                                                            |                                                                                    |                             |
| 1-in-x          | Present 1 in how many people are affected                                     | about 1 in 117                                                           | • Compare to known Risk / Peers / status quo                                      | • hard to understand |
|                 |                                                                               |                                                                          |                                                                                    | • wrong intuition |
|                 |                                                                               |                                                                          |                                                                                    | • widely discouraged |
| Odds            | \(\frac{xy}{y}\) with \(x\): revealed people participating, \(xy\): not revealed | The odds of being revealed by a statistics are 1.083.                     | always with: comparison to status quo                                              | • Not well understood for representation of risks |
|                 | people participating, \(x\): not revealed people participating \(y\): people revealed not participating \(yn\): people not revealed, not participating |                                                                          |                                                                                    |                             |
B STUDY RESOURCES

B.1 Welcome text

The aim of this survey is to evaluate the effectiveness of privacy notifications. It consists of up to 8 pages with 22 questions in total. We expect a working time of about 15 Minutes. It collects your response to a notification scenario, as well as some background information relevant to the analysis of your answers.

We collect no personal information except your gender. Since other studies identified influence of gender on the effectiveness of risk communication, we want to test if this is similar in our scenario. For this reason, we ask you to indicate your gender for a gender-specific analysis of the result.

Additionally, we automatically collect your IP address and the MTurk-IDs for quality assurance. After checking the data and approving the HIT towards Amazon Mechanical Turk, we will delete this data and your answer will be processed anonymously. All data collected from you will be used exclusively for study purposes and will not be passed on to third parties.

We record your response during your participation. If you change your mind and don’t want to continue to participate in the study, you can delete your answers by clicking the Button "Exit and clear survey".

Please do not use the browser navigation (for example the "back" button) during the survey. Please keep in mind that this survey aims to evaluate the effectiveness of the notification, not your performance or knowledge.

B.2 Scenario Description

You are a long-time customer of the ridesharing service "CityCar" in your home town. Recently, the CityCar app was updated. Since this update, you have not booked a ride, but today, you feel like booking a ride again – it is snowy, and public transport availability is limited.

After opening the app, you see a notification. Such notification is unfamiliar to you, before, the app had never shown such a notification.

The notification in the CityCar app informs you that aggregated statistics about the visited locations of all customers are transmitted to the Urban Redevelopment Authority. Such aggregated statistics include, for example, the "number of customers in the last month", which are reported for each location to the Urban Redevelopment Authority.

The notification also explains that the customer data will be used, among other things, to improve the urban infrastructure and public transport, especially in areas with high utilization of ridesharing services.

Together with this notification, you receive a short explanation of the potential privacy risk of you being re-identified in the aggregated statistics ...

B.2.1 Scenario-attention check questions.

- What kind of app is mentioned in the scenario?
  - Banking app
  - Car-Sharing app
  - Messaging app
- What kind of data is transmitted to the Urban Redevelopment Authority?
  - Location data
B.3 Understanding questions

B.3.1 Subjective Understanding.
- I have understood the notification.
- After reading the notification, I can assess my privacy risk, that is, the risk that the Urban Redevelopment Authority knows whether I visited a location or not after seeing the aggregated statistics.
- The notification provided all the information I wanted to know about the used technique (differential privacy).

B.3.2 Objective Understanding.
- In the scenario, the Urban Redevelopment Authority is less/more likely to know whether I visited the city hospital than if CityCar provided the unprotected data. (less)
- In the scenario, my risk of the Urban Redevelopment Authority knowing whether I visited the city hospital is higher/lower than if the CityCar app does not share any data. (higher)
- Without access to CityCar’s data, there is no risk that the Urban Redevelopment Authority will know whether I visited the city hospital. (false)
- In the scenario, the Urban Redevelopment Authority can determine whether I visited the city hospital or not. (false)

B.4 Privacy Risk Notifications

The wording of the 7 notifications is presented in Table 4 and an example of the visual representation is shown in Figure 7

C STATISTIC RESOURCES

The details results from the linear regression models are as follows:

C.1 Subjective Understanding

| Residuals: | Min | 1Q | Median | 3Q | Max |
|-----------|-----|----|--------|----|-----|
| -3.9382   | -0.6814 | 0.1885 | 0.7612 | 2.6016 |

| Coefficients: | Estimate | Std. Error | t value | Pr(>|t|) |
|---------------|----------|------------|---------|---------|
| (Intercept)   | 5.74347  | 0.55034    | 10.436  | <2e-16 *** |
| GruppeG1      | -0.60041 | 0.85960    | -0.704  | 0.4854  |
| GruppeG2      | -0.34916 | 0.73273    | -0.477  | 0.6341  |
| GruppeG3      | -1.37402 | 0.71574    | -1.915  | 0.0565 .|
| GruppeG4      | -0.96664 | 0.69193    | -1.403  | 0.1635  |
| GruppeG5      | -0.38527 | 0.74248    | -0.518  | 0.6083  |
| GruppeG6      | -1.56866 | 0.69863    | -2.245  | 0.0255 *|
| Numeracylowest| -0.05163 | 0.58916    | -0.088  | 0.9302  |
| Numeracylow   | -0.10838 | 0.69311    | -0.156  | 0.8758  |
| Numeracyhigh  | -0.65603 | 0.70904    | -0.925  | 0.3556  |
| P_binnedniedrig | -0.02355 | 0.71636     | -0.033  | 0.9738  |
| P_binnedhoch  | -0.22716 | 0.48733     | -0.455  | 0.6506  |
| Genderfemale  | 0.33080  | 0.41217     | 0.801   | 0.4239  |
| GruppeG1:Numeracylowest | 0.94925 | 0.78833     | 1.204   | 0.2295  |
| GruppeG2:Numeracylowest | 0.68041 | 0.73383     | 0.823   | 0.4111  |
“Am I Private and If So, How Many?”

| Condition  | Notification wording |
|------------|----------------------|
| FreqPure   | To respect your personal information privacy and ensure best user experience, the data shared with the app will be processed via the differential privacy technique. With differential privacy, at most 26 out of 50 statistics will reveal whether you visited a location. |
| FreqPosNeg | To respect your personal information privacy and ensure best user experience, the data shared with the app will be processed via the differential privacy technique. With differential privacy, at most 26 out of 50 statistics will reveal whether you visited a location. For 24 out of 50 statistics, however, your visit remains undetected. |
| FreqStatQuo| To respect your personal information privacy and ensure best user experience, the data shared with the app will be processed via the differential privacy technique. With differential privacy, at most 26 out of 50 statistics will reveal whether you visited a location. In comparison, by guessing without knowledge from the statistics, your visit would be revealed in 25 out of 50 statistics, which is only marginally different from the case with the statistics. |
| PercPure   | To respect your personal information privacy and ensure best user experience, the data shared with the app will be processed via the differential privacy technique. With differential privacy, at most 52% of the statistics will reveal whether you visited a location. |
| PercPosNeg | To respect your personal information privacy and ensure best user experience, the data shared with the app will be processed via the differential privacy technique. With differential privacy, at most 52% of the statistics will reveal whether you visited a location. In 48% of the statistics, however, your visit remains undetected. |
| PercStatQuo| To respect your personal information privacy and ensure best user experience, the data shared with the app will be processed via the differential privacy technique. With differential privacy, at most 52% of the statistics will reveal whether you visited a location. In comparison, by guessing without knowledge from the statistics, your visit would be revealed in 50% of the statistics, which is only marginally different from the case with the statistics. |
| BaseLine   | To respect your personal information privacy and ensure best user experience, the data shared with the app will be processed via the differential privacy technique. That is, the app company will store your data but only use the aggregated statistics with modification so that your personal information cannot be learned. However, your personal information may be leaked if the company’s database is compromised. |

Table 4. Notification Conditions

| Gruppe G1: Numeracylowest | 0.67367 | 0.74873 | 0.900 | 0.3690 |
|---------------------------|---------|---------|-------|--------|
| Gruppe G2: Numeracylowest | 0.92976 | 0.74979 | 1.240 | 0.2160 |
| Gruppe G3: Numeracylowest | 0.21832 | 0.74455 | 0.293 | 0.7696 |
| Gruppe G4: Numeracylowest | 1.37512 | 0.76692 | 1.793 | 0.8740 |
| Gruppe G5: Numeracylowest | 0.63758 | 1.02592 | 0.621 | 0.5348 |
| Gruppe G6: Numeracylowest | 0.42610 | 0.92291 | 0.462 | 0.6447 |
| Gruppe G7: Numeracylowest | 0.84179 | 0.94395 | 0.892 | 0.3732 |

| Gruppe G1: Numeracylow | 0.84179 | 0.94395 | 0.892 | 0.3732 |
|------------------------|---------|---------|-------|--------|
| Gruppe G2: Numeracylow | 1.57894 | 0.93863 | 1.697 | 0.8908 |
| Gruppe G3: Numeracylow | -0.28900 | 0.93189 | -0.310 | 0.7567 |
| Gruppe G4: Numeracylow | -0.36457 | 1.07912 | -0.338 | 0.7357 |
| Gruppe G5: Numeracylow | -0.25199 | 1.00130 | -0.252 | 0.8815 |
| Gruppe G6: Numeracylow | 0.58184 | 0.98730 | 0.589 | 0.5561 |
| Gruppe G7: Numeracylow | -0.36557 | 0.96798 | -0.378 | 0.7860 |

| Gruppe G1: Numeracyhigh | -0.25199 | 1.00130 | -0.252 | 0.8815 |
|-------------------------|---------|---------|-------|--------|
| Gruppe G2: Numeracyhigh | 0.58184 | 0.98730 | 0.589 | 0.5561 |
| Gruppe G3: Numeracyhigh | -0.36557 | 0.96798 | -0.378 | 0.7860 |
| Gruppe G4: Numeracyhigh | -0.25199 | 1.00130 | -0.252 | 0.8815 |
| Gruppe G5: Numeracyhigh | 0.58184 | 0.98730 | 0.589 | 0.5561 |
| Gruppe G6: Numeracyhigh | -0.36557 | 0.96798 | -0.378 | 0.7860 |
| Gruppe G7: Numeracyhigh | -0.25199 | 1.00130 | -0.252 | 0.8815 |

| Gruppe G1: P_binniedrig | 0.62718 | 0.91725 | 0.684 | 0.4947 |
|-------------------------|---------|---------|-------|--------|
| Gruppe G2: P_binniedrig | 0.21832 | 0.74455 | 0.293 | 0.7696 |
| Gruppe G3: P_binniedrig | 1.37512 | 0.76692 | 1.793 | 0.8740 |
| Gruppe G4: P_binniedrig | 0.63758 | 1.02592 | 0.621 | 0.5348 |
| Gruppe G5: P_binniedrig | 0.42610 | 0.92291 | 0.462 | 0.6447 |
| Gruppe G6: P_binniedrig | 0.84179 | 0.94395 | 0.892 | 0.3732 |
| Gruppe G7: P_binniedrig | 1.57894 | 0.93863 | 1.697 | 0.8908 |
| Gruppe G1: P_binniedrig | -0.28900 | 0.93189 | -0.310 | 0.7567 |
| Gruppe G2: P_binniedrig | -0.36457 | 1.07912 | -0.338 | 0.7357 |
| Gruppe G3: P_binniedrig | -0.25199 | 1.00130 | -0.252 | 0.8815 |
| Gruppe G4: P_binniedrig | 0.58184 | 0.98730 | 0.589 | 0.5561 |
| Gruppe G5: P_binniedrig | -0.36557 | 0.96798 | -0.378 | 0.7860 |
| Gruppe G6: P_binniedrig | -0.25199 | 1.00130 | -0.252 | 0.8815 |
| Gruppe G7: P_binniedrig | 0.58184 | 0.98730 | 0.589 | 0.5561 |
Fig. 7. Visual Representation: FreqStatQuo

C.2 Objective Understanding

Residuals:

| Min  | 1Q | Median | 3Q | Max  |
|------|----|--------|----|------|
| -2.40837 | -0.63293 | 0.00534 | 0.65711 | 2.35053 |

Coefficients:

| Estimate | Std. Error | t value | Pr(>|t|) |
|----------|------------|---------|---------|

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.264 on 291 degrees of freedom
Multiple R-squared: 0.2736, Adjusted R-squared: 0.1537
F-statistic: 2.283 on 48 and 291 DF, p-value: 1.577e-05
"Am I Private and If So, How Many?"

(Intercept)  1.613962  0.413580  3.902  0.000118  ***   
GruppeG1  0.241088  0.645981  0.374  0.708664   
GruppeG2 -0.025616  0.558644 -0.047  0.962928   
GruppeG3  0.288895  0.539228  0.521  0.602818   
GruppeG4  0.428408  0.519981  0.824  0.410685   
GruppeG5  0.036928  0.557970 -0.066  0.947278   
GruppeG6 -0.071511  0.520619 -0.136  0.891752   
Numeracylowest 0.241608  0.645981  0.374  0.708664   
Numeracylow -0.025616  0.558644 -0.047  0.962928   
Numeracyhigh  0.288895  0.539228  0.521  0.602818   
P_binnedniedrig  0.428408  0.519981  0.824  0.410685   
P_binnedhoch  0.036928  0.557970 -0.066  0.947278   
Genderfemale  0.046542  0.309742  0.150  0.880664   
GruppeG1:Numeracylowest -0.501209  0.550867 -0.910  0.363652   
GruppeG2:Numeracylowest -0.084992  0.562670 -0.151  0.880040   
GruppeG3:Numeracylowest -0.093785  0.563465 -1.664  0.097102 .   
GruppeG4:Numeracylowest  0.022382  0.693562  0.324  0.747731   
GruppeG5:Numeracylowest  0.065419  0.576340  0.114  0.909706   
GruppeG6:Numeracylowest -0.885753  0.699360 -1.267  0.206340   
GruppeG1:Numeracylow -0.468561  0.727434 -0.644  0.520818   
GruppeG2:Numeracylow  0.007763  0.439812  0.017  0.985930   
GruppeG3:Numeracylow  0.286116  0.789373  0.364  0.715758   
GruppeG4:Numeracylow  0.148045  0.793112  0.191  0.848324   
GruppeG5:Numeracylow -0.330996  0.767302 -0.430  0.668005   
GruppeG6:Numeracylow -0.187067  0.715112  0.262  0.793822   
GruppeG1:Numeracyhigh -0.093785  0.563465 -1.664  0.097102 .   
GruppeG2:Numeracyhigh -0.897788  0.741947 -1.210  0.227248   
GruppeG3:Numeracyhigh  0.458249  0.727434  0.639  0.520818   
GruppeG4:Numeracyhigh  0.127134  0.767302  0.166  0.868516   
GruppeG5:Numeracyhigh -1.195565  0.794288 -1.505  0.133356   
GruppeG6:Numeracyhigh -0.265667  0.738201 -0.364  0.716252   
GruppeG1:P_binnedniedrig  0.210960  0.627365 -0.336  0.736915   
GruppeG2:P_binnedniedrig  0.356772  0.435031  0.820  0.412826   
GruppeG3:P_binnedniedrig  0.007763  0.439812  0.017  0.985930   
GruppeG4:P_binnedniedrig -0.266738  0.444259  0.590  0.554701   
GruppeG5:P_binnedniedrig -0.330996  0.767302 -0.430  0.668005   
GruppeG6:P_binnedniedrig -0.469945  0.462353  1.016  0.312274   
GruppeG1:Genderfemale -0.939536  0.456398 -2.033  0.043343 *   
GruppeG2:Genderfemale  0.239658  0.418158  0.570  0.570791   
GruppeG3:Genderfemale -0.356772  0.435031  0.820  0.412826   
GruppeG4:Genderfemale -0.093785  0.563465 -0.644  0.520818   
GruppeG5:Genderfemale  0.576082  0.426563  1.351  0.177898   
GruppeG6:Genderfemale  0.208138  0.457393  0.447  0.654907   

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Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.9499 on 291 degrees of freedom
Multiple R-squared: 0.1655, Adjusted R-squared: 0.02785
F-statistic: 1.202 on 48 and 291 DF, p-value: 0.1825