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Can We Get Rid of Bias? Mitigating Systematic Error in Data Donation Studies through Survey Design Strategies

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Abstract
Digital trace data retrieved via data donations holds significant potential for the study of individual behavior. However, data donation studies may be subject to bias. Researchers therefore need to quantify and address systematic error in digital trace data. To complement a-posteriori error correction methods like statistical modeling, we tested how ex-ante approaches, in particular survey design strategies, may help address bias in data donation studies. We conducted two preregistered experiments, one with a convenience sample of students (N_I = 345) and one with a convenience sample from an online access panel (N_{II} = 2,039). In both experiments, we analyzed the effects of survey design strategies – technical support during data donation, personalized incentives, and highlighting the societal relevance of participants' data – on nonresponse rates and nonresponse bias. Our results indicate that while data donation studies are prone to both, our ex-ante strategies could not effectively decrease nonresponse rates or nonresponse bias. Overall, our study underlines the need to (a) make bias in digital trace data more transparent and (b) advance research on error correction methods.

Keywords: Data Donation, Digital Trace Data, Error, Bias, Nonresponse, Error Correction Methods, Survey Design

Introduction

Social scientists are increasingly relying on computational methods to integrate the collection of digital trace data in surveys. In tracking studies, users provide data via apps or browser plugins before or after providing self-reported data via a survey (e.g., Jürgens et al., 2020). Linkage studies rely on users sharing their social media handles with researchers, who then collect their data via APIs (e.g., Beuthner et al., 2024). In sensor studies, researchers ask users to share their data, for example images via smartphone cameras (e.g., Struminskaya et al., 2021). As a more recent approach, researchers may rely on data donation studies. In accordance with the General Data Protection Regulation, users download data which platforms collect on them in the form of Data Donation Packages (DDPs). Users then share their data with researchers using data donation tools (Araujo et al., 2022; van Driel et al., 2022). Data donation studies have become an essential staple for studying smartphone use (Ohme et al., 2021) and social media behavior (van Driel et al., 2022).

In tandem with debates about bias related to computational methods, potential pitfalls in data donation studies have come to light in recent years. These include low response rates, as fewer people participate in data donation studies compared to tracking or linkage (Silber et al., 2022). At best, low response rates increase the cost of recruiting large and representative samples. At worst, they invite sample-related bias (Groves & Peytcheva, 2008). For example, participants with lower technical skills are less likely to provide data (Jäckle et al., 2019; Ohme et al., 2021). If technical skills correlate with dependent variables, such as online information behavior, the nonresponse of less savvy respondents may bias the consistency, size, and direction of estimates.

Consequently, scholars are increasingly systematizing (Boeschoten et al., 2022) and quantifying bias in digital traces (Jürgens et al., 2020; Ohme et al., 2021). In an attempt to improve transparency and address bias, they have developed ex-ante error correction methods, such as statistical modeling, to correct bias after data collection (Pak et al., 2022). However, this begs the question of whether researchers can also tackle the emergence of bias via ex-ante error correction methods before data collection. Survey design strategies, for instance offering incentives or technical support to participants, are examples of related approaches. Nevertheless, analyses of the effects of ex-ante methods and especially how they affect participation in data donation studies are rare (for exceptions, see Keusch et al., 2024; Silber et al., 2022).

To quantify and address sample-related bias in data donation studies, we conducted two preregistered experiments embedded within a data donation study on how German social media users engage with news[1]. We drew on a convenience sample of students (Study I, N_{II} = 345) and a convenience sample from an online access panel (Study II, N_{II} = 2,039). After quantifying

[1]We thank MA students at LMU Munich who participated in data collection as well as Theo Araujo for feedback on the project.

nonresponse rates and nonresponse bias, we tested whether survey design strategies can mitigate bias.

Our study contributes to research streams on bias related to computational methods, particularly in the context of digital trace data. First, we introduce a distinction between a-posteriori and ex-ante error correction methods as different means of addressing bias. Second, we enrich the knowledge on bias in self-reported intentions to provide data, which are often studied via vignette experiments (e.g., Kmetty et al., 2024; Pfiffner & Friemel, 2023), through empirical evidence on actual behavior. Third, we extend the knowledge on how bias in surveys and data donation studies may differ and thus contribute to the conceptualization of future data donation studies. Overall, our study demonstrates that researchers should not only make bias in data donation studies—and digital trace data more generally—more transparent, but they also need to adapt existing error correction methods and develop new ones to address bias.

Bias in Data Donation Studies

Any empirical study includes error, that is, deviations from the true value of a theoretical concept introduced by its measurement. Non-systematic error resembles random deviations that influence the variance of estimates, while systematic error, also called bias, depends on omitted variables. Bias influences observed means or variances, thereby potentially attenuating or inflating inferential conclusions (Peytchev, 2013).[2] To understand bias in data donation studies, we first discuss types of bias and then turn to error correction methods.

Defining Bias

To decompose bias, scholars traditionally rely on the Total Survey Error (TSE) framework (Groves & Lyberg, 2010). While sample-related bias may emerge due to inadequate sampling or systematic nonresponse, measurement-related bias, for example, entails invalid operationalizations. Data donation studies differ from surveys in that, in the former, platforms determine data availability and measurements. This leads to a lack of relevant data and poor documentation (Haim & Hase, 2023), which leaves researchers with little control over measurement-related bias. Consequently, we focus on sample-related bias in the remainder of this paper.

[2]We use the terms “bias” and (systematic) “error” interchangeably throughout the paper.

Boeschoten et al. (2022) adapted the TSE framework to the context of data donation studies to disentangle the different types of sample-related bias in digital trace data. In Figure 1, we extend their framework by depicting error correction methods. To illustrate, we ask how German social media users engage with news on social media, that is, how they comment on, search for, like, (un)follow, or block news. How can scholars study this question via data donations and what types of bias may emerge in this context?

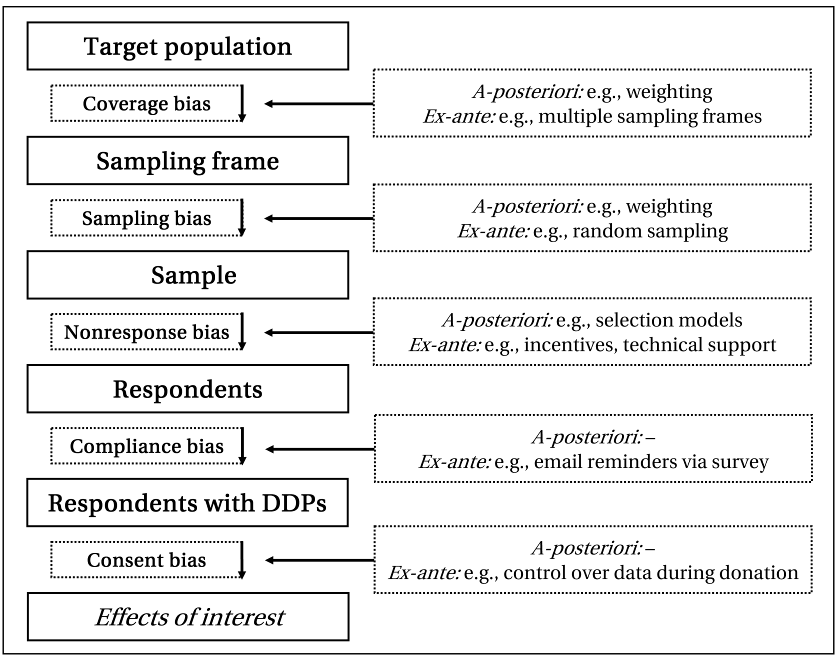

Figure 1: Sample-Related Bias in Data Donation Studies. Adapted based on Boeschoten et al. (2022).

According to Boeschoten et al. (2022), sample-related bias comprises five types of bias. These emerge due to the characteristics of the respondents, the survey design, and the data donation tool. *Coverage bias* is introduced when the target population and the sampling frame differ. For example, users may have multiple accounts on the same platform, which may lead to relevant units of analysis being excluded. Researchers may be unable to rely on random sampling, which is relatively expensive, and convenience sampling introduces *sampling bias.* Participants may also be subject to self-selection. For example, participants with less technical skills may be unable or unwilling to participate (Gil-López et al., 2023; Jäckle et al., 2019).

If variables correlated with dropout, such as technical skills, also correlate with dependent variables (e.g., how people use social media), this leads to *nonresponse bias*. After participants request their data from platforms, it often takes several days for them to receive their DDPs. If respondents systematically decide against participation while waiting for their data, this results in *compliance bias*. Notwithstanding, once compliant, respondents may drop out when presented with the data they are about to donate, which introduces *consent bias*.

Bias related to coverage, sampling, or nonresponse are well-known issues in survey research (Groves & Lyberg, 2010). Consequently, researchers can partly rely on frameworks like the TSE to understand bias in data donation studies. However, as already indicated by Boeschoten et al. (2022), they must adapt existing frameworks to account for new types of bias, such as those related to compliance or consent. Moreover, sample-related bias is potentially more challenging, if not impossible, to detect in data donation studies compared to surveys. Lists of the target population or the sampling frame (e.g., of all German social media users) are often inaccessible. It may also be unclear whether responses are missing because participants were not willing to provide data (nonresponse bias) or whether they downloaded their data but did not upload it (compliance or consent bias). In addition, different types of bias may reinforce (Jäckle et al., 2019) or mask one another (Struminskaya et al., 2021).

Survey research (Peytchev, 2013) has shown that bias may not only influence observed means or variances but also inferential conclusions. However, research in the context of digital trace data has primarily focused on biased means or variances (see critically Pak et al., 2022), for instance, by describing bias in estimated platform or device use (Keusch et al., 2024; Ohme et al., 2021). However, Pak et al. (2022) illustrated that sample-related bias may also influence the size and direction of effects in downstream inferential analysis (see similarly Bosch et al., 2023; Jürgens et al., 2020). As such, mere transparency about bias in digital traces is insufficient; researchers also need to address such bias (TeBlunthuis et al., 2024).

Addressing Bias via Error Correction Methods

Following the tradition of error correction methods in survey research (Buonaccorsi, 2010; Peytchev, 2013), scholars have also discussed (Boeschoten et al., 2022) and adapted (Pak et al., 2022) error correction methods for data donation studies. To better distinguish between existing approaches, we propose differentiating between a-posteriori and ex-ante error correction methods.

A-posteriori error correction methods are implemented after data collection, often via statistical modeling. They mainly address bias by accounting for respondent-related characteristics that may induce bias in descriptive and inferential results through global (e.g., weighting) and outcome-specific adjustments (e.g., selection models). For example, Pak et al. (2022) tested how weighting and selection models can correct for nonresponse bias in data donation studies. In a similar vein, Keusch et al. (2023) used weighting to adjust for coverage bias in tracking studies. However, a-posteriori approaches rely on often untestable assumptions. For instance, researchers need to include exogenous variables based on which bias is to be corrected. Not only is the assumption of exogeneity hard to test, but researchers may also lack access to the relevant variables predicting self-selection. For example, compliance bias introduced by participants waiting for DDPs and thus forgetting to donate is difficult to address statistically because researchers cannot approximate how long the participants waited across platforms.

In contrast, *ex-ante error correction methods* are implemented before data collection. They focus on changing characteristics related to the survey or data donation tool to address bias before it emerges. With ex-ante approaches, researchers aim to reach a less biased sample, which may in turn lead to less biased descriptive and inferential results. Ex-ante approaches can take the form of survey design strategies (e.g., offering incentives) or adapted data donation tools (e.g., offering participants control over their data). Examples of ex-ante approaches include more varied sampling to address coverage bias (similar to multiple sampling frame approaches; Peytchev, 2013) or random sampling to address sampling bias. Nonresponse and compliance bias, that is, participants dropping out because they are not willing or able to provide data, may be mitigated by offering financial incentives (Kmetty et al., 2024; Silber et al., 2022), changing the framing of the donation request (but see Keusch et al., 2024), or automatically scheduling emails to remind participants to donate data (Boeschoten et al., 2022). Design choices for the data donation tools, such as allowing users to remove data, may similarly address consent bias (for the context of sensor data, see similarly Struminskaya et al., 2021). To date, ex-ante strategies have mostly been tested in relation to linkage (Beuthner et al., 2024), sensors (Struminskaya et al., 2021), and tracking (Silber et al., 2022) but less for data donation (for recent exceptions, see Keusch et al., 2024; Silber et al., 2022). More generally, it is unclear whether scholars can adapt error correction methods from survey research or whether they need to develop new methods for data donation contexts.

Nonresponse Bias in Data Donation Studies

In this study, we focus on quantifying and addressing a single sample-related bias[3]: nonresponse bias. Researchers have found overwhelming evidence of low response rates when participants have been asked to provide digital traces via tracking (Gil-López et al., 2023; Jürgens et al., 2020) or sensors (Struminskaya et al., 2021). Worryingly, even lower participation has been reported in data donation studies, with response rates between 1% and 38% (e.g., Keusch et al., 2024; Ohme et al., 2021; Silber et al., 2022). Apart from increasing the costs of recruitment, the results may be biased, as nonresponse can—but does not have to—indicate nonresponse bias (Groves & Peytcheva, 2008). This would contradict the use of digital traces as a "gold standard" for enriching and validating survey-based measures.

Quantifying Bias

To understand nonresponse bias, researchers can partly draw upon established theories in survey research (for an overview, see Keusch, 2015). According to social exchange theory, people participate in surveys because they trust that the expected rewards will outweigh the expected costs (Dillman, 1978). This extends to data donation studies, where much like surveys (Singer & Ye, 2013), financial incentives, for example, have been found to increase response rates (Kmetty et al., 2024; Silber et al., 2022). At the same time, researchers should consider additional mechanisms that may induce nonresponse bias. Due to the multitude of steps necessary to request, download, and donate data, the expected burden in data donation studies likely exceeds that of surveys. Moreover, different mechanisms may be at play. Drawing on the Technology Acceptance Model by Davis (1985), Wenz and Keusch (2023) stress that participation also relies on how respondents perceive the ease of use of data donation tools (in line with the expected burden) and their usefulness (in line with the expected rewards), which differentiates data donation studies from surveys.

Pertinent research explains nonresponse rates (i.e., how many participants decide against providing data) and nonresponse bias (i.e., whether participants who provide data differ systematically from those who do not) based on respondent-related characteristics. Overall, *sociodemographic*

[3]We also preregistered two RQs on coverage bias. However, we agree with the issues raised during the review, namely, that answering these RQs is not possible with the preregistered design. For full transparency, our preregistration on this aspect, the preliminary results we submitted for review in the first draft of our paper and an anonymized, shortened version of the reviewers' comments are available in the Appendix (Supplement, Element A2).

characteristics bear little correlation with whether participants provide digital trace data via sensors (Struminskaya et al., 2021), tracking (Gil-López et al., 2023; Jäckle et al., 2019), linkage (Silber et al., 2022), or data donation (Keusch et al., 2024; Ohme et al., 2021). In terms of *attitudes toward politics*, however, studies have indicated that politically interested participants and those to the political left are more likely to provide data (Gil-López et al., 2023; but see Pak et al., 2022). Moreover, *technology- and privacy-related attitudes* play a role. While there is limited evidence that respondents drop out due to general privacy concerns (Ohme et al., 2021; but see Keusch et al., 2024; Pak et al., 2022; Silber et al., 2022), technical difficulties in providing data are a more consistent predictor (Gil-López et al., 2023; Jäckle et al., 2019). Correspondingly, skills concerning devices or platforms at least partly correlate with whether participants provide data (Jäckle et al., 2019; Ohme et al., 2021; Silber et al., 2022). For our study, with its focus on news engagement on social media, users' awareness and appreciation of algorithms would be more specific predictors. Algorithmic awareness is "*a meta-skill*, a knowledge or understanding that may improve other digital skills" (Gran et al., 2021, p. 1791). Algorithmic appreciation, in turn, is a consequence of algorithmic awareness and interlaces with users' news engagement online (Schaetz et al., 2023). As such, people who differ in algorithmic awareness and appreciation may also differ in how they use platforms, which makes systematic dropout related to such variables especially cumbersome. *Social media use* may also predict nonresponse and, due to its overlap with measures of interest, indicate nonresponse bias. Here, the frequency of use seems less important in explaining dropout than how users perceive and use platforms (Keusch et al., 2024; Pak et al., 2022; Pfiffner & Friemel, 2023).

However, research on nonresponse bias in data donation studies is limited. First, underlying mechanisms driving such bias have largely been tested in other contexts, such as linkage, sensors, or tracking studies. Second, existing studies often test nonresponse related to donation intentions rather than actual participation. Third, the existing research largely quantifies nonresponse rates instead of nonresponse bias. Thus, we ask:

RQ1: *How prevalent is nonresponse bias in data donation studies?*

Addressing Bias: Survey Design Strategies

To address nonresponse bias, we focus on three survey design strategies: technical face-to-face support, personalized incentives, and underlining the societal relevance of data donations.

Technical Face-to-Face Support During Data Donation

Technical difficulties rarely increase nonresponse rates in surveys (Peytchev, 2013) but may constitute a more pronounced problem in data donation studies. Participants are not likely to be familiar with requesting, finding, and uploading data. In a representative study in Switzerland, Pfiffner and Friemel (2023) found that only 8% of participants ever requested their DDPs. Relatedly, study participants have frequently mentioned technical difficulties as a reason for nonresponse (Gil-López et al., 2023; Jäckle et al., 2019).

Drawing on the Technology Acceptance Model, providing technical support could alleviate such issues and improve the perceived ease of use of data donation tools (Wenz & Keusch, 2023). Based on a study with young adolescents, van Driel et al. (2022) recommend meeting with participants to instruct them on the technicalities of the donation process. Providing support in person could strengthen participants' trust in the process given that, in line with social exchange theory, a lack of such trust—and trust in research in general—correlates with high nonresponse rates (Keusch et al., 2024; Makhortykh et al., 2021). Similarly, in-person survey modes may partly increase participation in providing digital traces (Al Baghal et al., 2020; but see Jäckle et al., 2019). However, empirical evidence on the effects of face-to-face technical support is scarce. In a vignette experiment on participation in tracking studies, Wenz and Keusch (2023) concluded that the participation of people invited by an interviewer, who also guided them through the installation process, decreased participation by two percentage points compared to participants who received instruction via a letter. Importantly, this effect did not vary alongside participants' technical skills. As this ex-ante method has not been tested in the context of data donation, we ask:

RQ2a: *Can we mitigate nonresponse bias in data donation studies by providing technical face-to-face support?*

Offering Personalized Incentives

In line with social exchange theory, monetary incentives increase perceived rewards and thus survey participation (Singer & Ye, 2013). Research has shown similar effects for studies that include linkage (Silber et al., 2022; but see Beuthner et al., 2024), tracking (Keusch et al., 2019; but see Jäckle et al., 2019), and data donation (Kmetty et al., 2024; Silber et al., 2022). Since financial resources may be limited and not motivate all participants to the same degree (Kmetty et al., 2024), researchers could also rely on personalized incentives. While these have had limited effects in surveys (Keusch, 2015), the outcomes may differ for data donation studies: Participants have stressed that they are more likely to provide digital traces in exchange for personalized results on their behavior (Makhortykh et al., 2021). Moreover, participants perceive visual summaries of their digital traces to be highly informative (Menchen-Trevino, 2016).

In line with the Technology Acceptance Model, (Wenz & Keusch, 2023) argue that personalized reports may increase the perceived usefulness of data donation tools and, in turn, participation. How participants use or perceive platforms also partly correlates with whether they intend to or actually donate data (Pak et al., 2022; Pfiffner & Friemel, 2023; Silber et al., 2022). In particular, Keusch et al. (2024) found that respondents with lower trust in Facebook were more likely to share data from this platform, presumably “to learn more about what information Facebook had about them” (p. 10). If platform use and perception correlate with participation, obtaining a summary report of one’s platform activities may increase participation because participants want to know what data platforms collect on them.

To date, empirical evidence on personalized incentives has been mixed: Pilgrim and Bohnet-Joschko (2022) noted that offering personalized incentives had no effect on respondents’ willingness to participate in tracking studies. In their mobile app study, Wenz et al. (2022) established that personalized incentives had limited effects on perceived survey burden and no effects on actual participation, a result Wenz and Keusch (2023) confirmed for tracking. In contrast, Kmetty et al. (2024) found that, at least in the US, personalized incentives increased respondents’ intention to participate in data donation. Given these mixed results, we ask:

RQ2b: *Can we mitigate nonresponse bias in data donation studies by offering personalized incentives?*

Underlining the Societal Relevance of Data Donations

Sensitive questions can influence survey participation (Tourangeau & Yan, 2007), especially related to their wording. A data donation request could be considered a sensitive question in data donation studies. In accordance with social exchange theory, researchers requesting data donations may increase expected rewards and motivate respondents by emphasizing the relevance of their data, seeing that the purpose of data may shape donation intentions (Bach et al., 2024). Again, empirical evidence on this ex-ante strategy is mixed. In terms of data-sharing intentions, the wording of sharing requests in linkage studies influences participants' intentions to participate (Fobia et al., 2019). Similarly, Pfiffner and Friemel (2023) showed that participants have a stronger intention to donate their data if they perceive the data to be relevant for research. However, this strategy seems less effective in shifting actual behavior. Beuthner et al. (2024) found that highlighting the relevance of participants' data—either for themselves or science—does not influence whether they provide data via linkage. Struminskaya et al. (2021) reached a similar conclusion when studying the intention to and actual participation in sensor studies. Moreover, Keusch et al. (2024) found that characterizing survey data in DDPs as more valuable does not influence participation in data donation studies. Researchers have largely tested the reframing of data requests in terms of their relevance to participants (Beuthner et al., 2024; Struminskaya et al., 2021) or science (Beuthner et al., 2024; Keusch et al., 2024) but not society. We thus ask:

RQ2c: *Can we mitigate nonresponse bias in data donation studies by explaining the societal relevance of data donations?*

Method and Data

We conducted two between-subject experiments (Study I, Study II) that were embedded in a data donation study in Germany. Our study was preregistered and approved by the institutional review board at the Department of Media and Communication at LMU Munich. In the Supplement (https://osf.io/vfazc), we provide our preregistered report (Supplement, Element A1), any deviations from which are made transparent (Supplement, Element A2) based on the guidelines of Willroth and Atherton (2024). We share details on our experimental stimuli (Element A3), measures (Element A4), and analyses (Element A5), as well as our data and code for reproducibility (Element A6).

Procedures

For both studies, we first used an online survey to measure the participants' sociodemographic characteristics, attitudes toward politics, technology- and privacy-related attitudes, and self-reported social media use. We then asked the participants whether they were willing to participate in a data donation (intention to donate data) before asking them to donate their data (participation in data donation). The participants could provide DDPs for up to four of the most-used social media platforms in Germany at that time (i.e., in late 2022): Facebook, Instagram, Twitter, and YouTube (Newman et al., 2022). For the donation, we relied on a newly developed software solution to integrate the data donation tool, OSD2F (Araujo et al., 2022), in the survey software SoSci Survey (Haim et al., 2023). From the users' DDPs, we extracted information on which news they had commented on, searched for, liked, (un)followed, or blocked. Using the data donation tool, we anonymized the engagement indicators based on whitelists and transformed them into either non-news-related ("You started following <USER>") or news-related ("You started following Tagesschau"). The participants could upload, inspect, and delete their data before being asked to provide informed consent to ultimately donate their data (for further information on the data donation tool, see Supplement, Appendix A4.1). Lastly, the participants were invited to participate in a lottery, in which they could win a 10-euro gift voucher for survey participation or a 50-euro gift voucher for donating their data.

Samples

Study I followed a 3×2 between-subjects design (experimental factors: *Technical Face-to-Face Support During Data Donation*, *Personalized Incentives*). It was based on a convenience sample of students at universities in Germany. We approached students in person, mostly around lectures. Data was collected between November 2022 and January 2023. Based on a power analysis ($1–\beta = .80$, $\alpha = .05$), we aimed to collect 504 completed surveys (i.e., participants finishing the survey and reaching the introduction to the data donation). Even after extending the data collection period for a month, we only accumulated $N_{\mathrm{I}} = 345$ surveys. Study I is underpowered.

Study II was built on a 2×2 between-subjects design (experimental factors: *Personalized Incentives*, *Underlining the Societal Relevance of Data Donations*) and based on the SoSci Survey online convenience panel (Leiner, 2016). The invitations were sent via email and the data was collected between November 2022 and January 2023. Based on a power analysis ($1–\beta = .80$, $\alpha = .05$), we aimed for 1,500 surveys. However, the response rate was higher and Study II included $N_{\mathrm{II}} = 2{,}039$ participants. Study II is overpowered, the main consequence of which is potentially detecting significant yet trivial effects.

Experimental Factors and Stimulus Material

The experimental factors included our three ex-ante error correction methods: *Technical Face-to-Face Support During Data Donation*, *Personalized Incentives*, and *Underlining the Societal Relevance of Data Donations*.

Technical Face-to-Face Support During Data Donation

With regard to RQ2a, the participants were assigned one of three conditions: (1) no support, with the participants requesting data only via written instructions (control group); (2) mandatory face-to-face technical support for requesting data; or (3) mandatory face-to-face technical support for uploading data. Unlike the other experimental factors, this treatment was included after participants had stated their willingness to participate in the data donation. They could choose whether they wanted to receive support right away or at a later date of their choice (with several time slots available each day over several weeks after their survey participation). Due to COVID-19 restrictions, we offered support either in-person or virtually based on the participants' preferences, with identical protocols for the support team (see Supplement, Element A3.1). *Technical Face-to-Face Support During Data Donation* was only included in Study I, as it was not feasible to provide face-to-face support to the larger online panel in Study II.

Offering Personalized Incentives

For RQ2b, the participants were assigned one of two conditions: (1) no personalized analysis (control group) or (2) a personalized analysis of their social media use. The experimental group was offered the latter option when being introduced to data donation. They received the prompt: "*We offer you a detailed and individualized analysis of your data. Based on our analysis, you will be able to see whether your individual media usage lies above or below the German average.*" For this incentive, we compared the participants' self-reported media use to the average use in Germany (Newman et al., 2022). Figure 2 includes an example (see further Supplement, Element A3.2). *Personalized Incentives* was included in Studies I and II.

Underlining the Societal Relevance of Data Donations

For RQ2c, the participants were assigned one of two conditions: (1) an explanatory video on data donations (control group) or (2) an explanatory video that additionally highlighted how a participant's donation could help society solve problems, such as the spread of fake news (for an excerpt, see Figure 3; full videos via Supplement, Element A3.3). The participants were exposed to this treatment when introduced to the data donation. *Underlining the Societal Relevance of Data Donations* was only included in Study II.

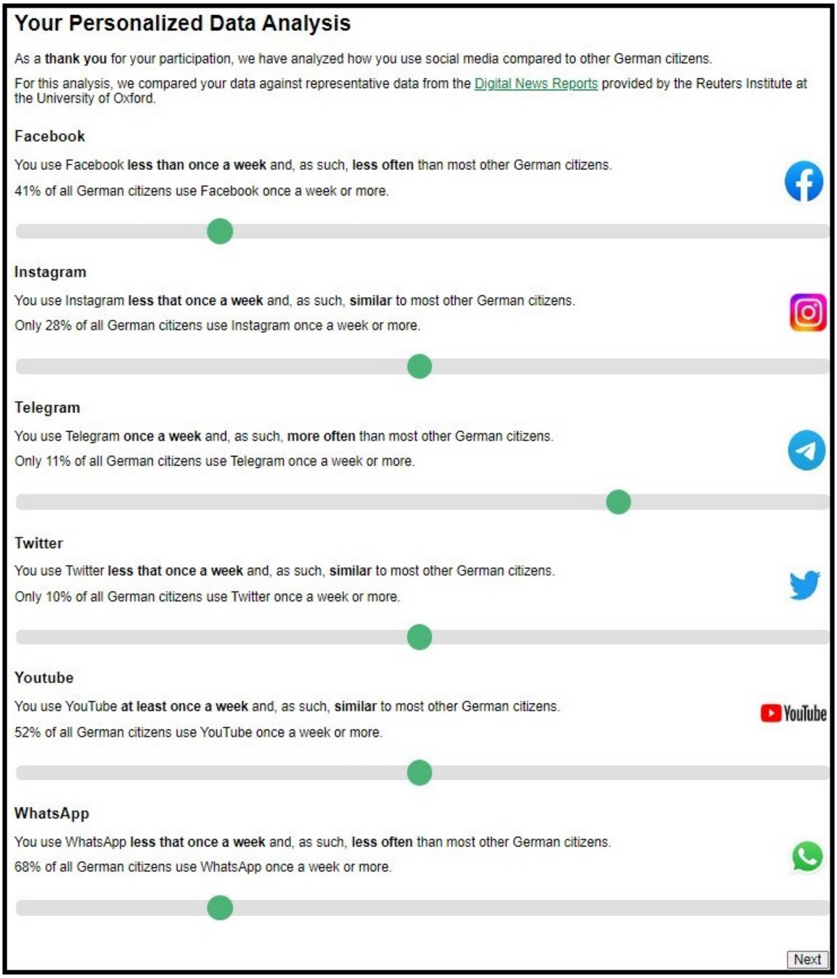

Figure 2: Personalized Incentive.

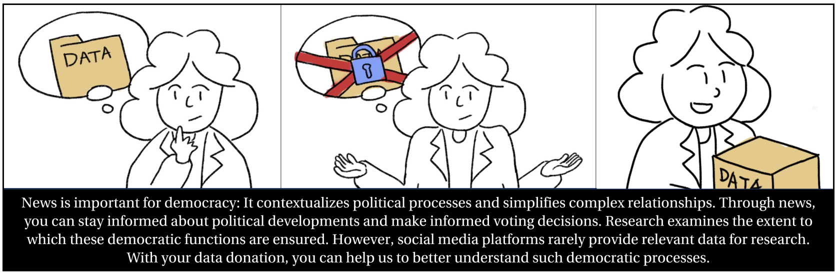

Figure 3: Explanatory Video Underlining the Societal Importance of Data Donations.

Measurements

For details on the measures, including the item wording, see Supplement, Elements A4.2 and 4.3. All the data from here on can be reproduced via our shared data and code (Element A6). Note that we differentiated between Study I and II (e.g., M_I vs. M_{II}) in the summary statistics.

Sociodemographic Characteristics

We determined the participants' *Age* (M_I = 22.8 years, SD_I = 5.9; M_{II} = 52 years, SD_{II} = 15.3), *Gender* (female: 66%$_I$, 54%$_{II}$), *Education* (university degree: 35%$_I$, 63%$_{II}$), and *Income* (3,500–4,500 EUR: 15%$_I$, 20%$_{II}$).

Attitudes Toward Politics

We assessed *Political Interest* using the five-item scale (M_I = 3.3, SD_I = 1.1, α_I = .92; M_{II} = 3.7, SD_{II} = 1, α_{II} = .92) of Otto and Bacherle (2011). *Political Orientation* was operationalized via a single item, where lower values indicated orientation to the left (M_I = 2.9, SD_I = 1; M_{II} = 3.1, SD_{II} = 1.3).

Technology- and Privacy-Related Attitudes

Algorithmic Appreciation was measured using the two-item scale (M_I = 2.9, SD_I = 0.9, α_I = .64; M_{II} = 2.3, SD_{II} = 1, α_{II} = .72) of Newman et al. (2016). *Awareness of Algorithmic Filtering* relied on a four-item scale (M_I = 4.5, SD_I = 0.6, α_I = .69; M_{II} = 4.4, SD_{II} = 0.8, α_{II} = .82) and *Awareness of Human-Algorithm Interplay* on a three-item scale (M_I = 4.4, SD_I = 0.7, α_I = .58; M_{II} = 4.4, SD_{II} = 0.7, α_{II} = .75) developed by Zarouali et al. (2021). We measured *Privacy Concerns* with a five-item scale (M_I = 3.5, SD_I = 0.9, α_I = .81; M_{II} = 3.7, SD_{II} = 0.9, α_{II} = .88) of Dobber et al. (2019). Lastly, we included one item for *Technical Skills* (M_I = 4.1, SD_I = 0.9; M_{II} = 3.7, SD_{II} = 1.1).

Social Media Use

We measured *Self-Reported Social Media Use* on a range of 1–5 (where 1 = never and 5 = daily) for the six most used platforms in Germany: Facebook, Instagram, Telegram, Twitter, YouTube, and WhatsApp.

Participation in Data Donation

After the participants had completed the survey, we asked whether they would be willing to donate their data (*Intention to Donate Data*: 63%$_I$, 52%$_{II}$).

We then measured whether the participants donated data for at least one platform (*Participation in Data Donation*: $20\%_{\mathrm{I}}$, $12\%_{\mathrm{II}}$), including the relative share of platforms for which they donated any data (*Degree of Participation in Data Donation*: $M_{\mathrm{I}} = 0.1$, $SD_{\mathrm{I}} = 0.2$; $M_{\mathrm{II}} = 0.1$, $SD_{\mathrm{II}} = 0.2$). The latter variable was standardized by accounting for platforms respondents reported using.

Analytic Strategy

For RQ1, we quantified the nonresponse rates across the different stages of the study. Second, we calculated nonresponse bias by comparing the proportion of the participants in the full sample with the proportion of donors (see similarly Keusch et al., 2019; Struminskaya et al., 2021). Metric variables were collapsed into binary categories or quantiles where necessary[4]. For example, if 50% of the survey respondents were female but only 45% of the donors were female, this would indicate a nonresponse bias of 5% related to gender. Following Lee (2006), we calculated the standard errors for z-tests on the consistency of nonresponse bias. Finally, we used logistic and linear regression models to understand which independent variables correlated with participation at different stages, with *Intention to Donate Data*, *Participation in Data Donation*, and *Degree of Participation in Data Donation* as dependent variables. To ease interpretation, we report average marginal effects (AME). For RQ2a–c, we relied on null models to test whether nonresponse rates and nonresponse bias changed across experimental conditions. We excluded variables that exhibited low reliability, such as *Algorithmic Appreciation* in Study I.

Results

Quantifying Nonresponse Bias (RQ1)

While 63% of the respondents in Study I and 52% in Study II stated that they would be willing to donate data (*Intention to Donate Data*), actual compliance was far lower. Only 20% of the participants donated data in Study I and 12% in Study II (*Participation in Data Donation*). In Study I, 59% of the donors provided information for a single platform, while 30% donated data for two and 10% for three. In Study II, 78% of the donors provided information for a single platform, while 16% donated data for two, 4% for three, and 2% for four (*Degree of Participation in Data Donation*).

[4]We used the third quantile, including the median value, as a reference category for *Age* and *Income*, while all the other non-binary variables were dichotomized. For further details, see the code in Appendix A6.

Apart from low response rates, we also recorded an average nonresponse bias of 7% for Study I and 6% for Study II when comparing the full sample of survey participants to the donors (i.e., the participants who also donated data). As shown in Figure 4 (see further Supplement, Element A5.1), the size and consistency of bias differed across the variables. We did not find consistent nonresponse bias in relation to sociodemographic variables. For political attitudes, however, the share of politically interested participants in Study I was 19% higher among the donors compared to the full sample of survey respondents ($p < .001$, n.s. for Study II). In both studies, the donors overrepresented participants who leaned toward the left ($\text{bias}_{\text{I}} = 16\%$, $p < .01$; $\text{bias}_{\text{II}} = 8\%$, $p < .01$). In terms of technology- and privacy-related attitudes, the donors tended to have higher technical skills ($\text{bias}_{\text{I}} = 11\%$, $p < .01$; $\text{bias}_{\text{II}} = 14\%$, $p < .001$) and algorithmic awareness ($\text{bias}_{\text{II}} = 8\%$, $p < .001$ for *Awareness of Algorithmic Filtering*; $\text{bias}_{\text{II}} = 5\%$, $p < .05$ for *Awareness of Human-Algorithm Interplay*). The donors also had lower privacy concerns ($\text{bias}_{\text{II}} = -10\%$, $p < .01$, n.s. for Study I). Lastly, we found consistent bias in self-reported social media use, at least in Study II: The participants who donated data used Facebook ($\text{bias}_{\text{II}} = 8\%$, $p < .01$), Instagram ($\text{bias}_{\text{II}} = 11\%$, $p < .001$), Twitter ($\text{bias}_{\text{II}} = 8\%$, $p < .01$), and YouTube ($\text{bias}_{\text{II}} = 10\%$, $p < .001$) more often compared to the full sample of survey respondents.

We further analyzed how individual characteristics correlated with the decision to donate data across different stages (selected results in Figure 5; see also Supplement, Element A5.2). While Figure 4 shows a comparison of the individual characteristics of all the survey participants and the subset of participants who donated data, Figure 5 depicts the (self-reported) decisions to donate data of the full sample.

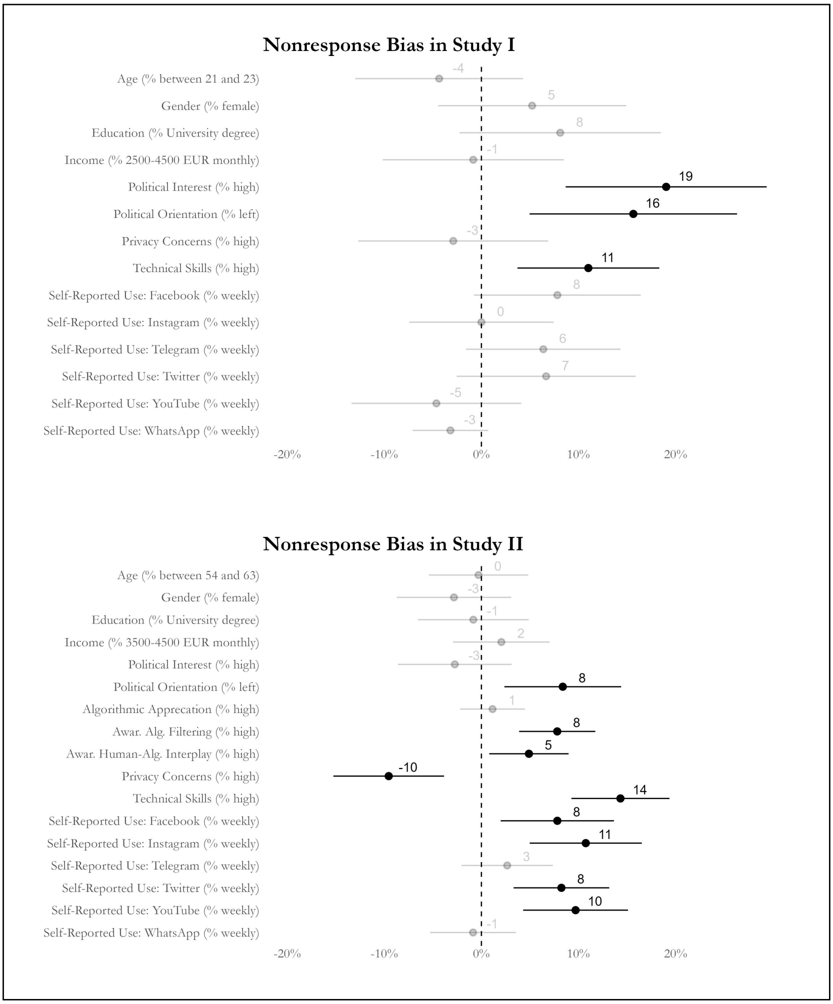

Figure 4: Nonresponse Bias. Depicts the estimated bias in proportions between the full sample of survey respondents and the participants who donated data. Consistent bias is depicted in black. As an example for interpretation, in Study I, the proportion of politically interested participants was 19% higher among the donors compared to the survey respondents.

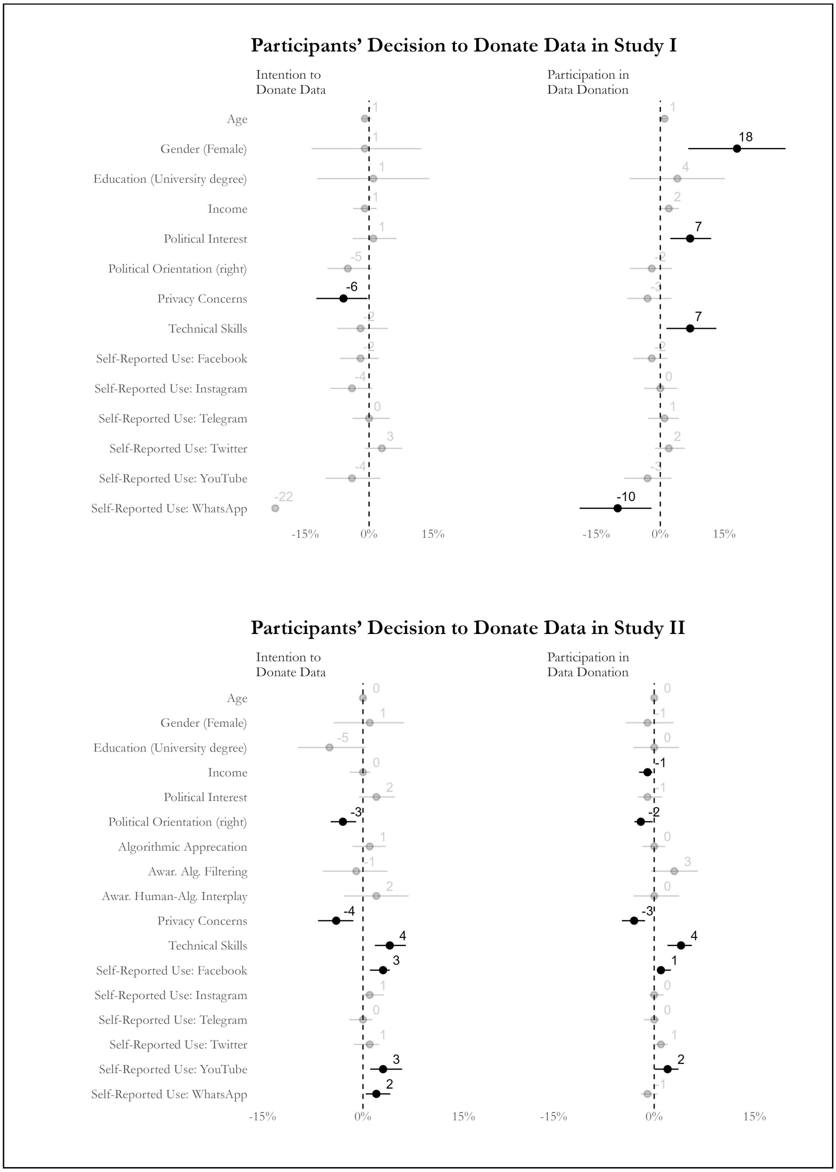

Figure 5: Explanation of Participants' Decisions to Donate Data Across Study Stages. For readability, we excluded the large confidence interval of *Self-Reported Use: WhatsApp* when modeling *Intention to Donate Data* in Study I (upper panel, left model). As shown, the effect was inconsistent. As an example for interpretation, the predicted probability with which the participants participated in the data donation increased by 7% for each point on the 1 to 5 scale for *Technical Skills* in Study I.

Although some effects were inconsistent in this slightly different analysis approach, we arrived at similar conclusions regarding how the individual characteristics correlated with participation. More importantly, however, relatively few differences were evident between the predictors of self-reported intentions (*Intention to Donate Data*) and actual behavior (*Participation in Data Donation*; Figure 5).

Across the measures, the most consistent predictors of self-reported intentions and actual participation in data donation studies were attitudes toward politics (i.e., political interest, political orientation), technology- and privacy-related attitudes (i.e., privacy concerns, technical skills), and social media use. Few characteristics, for example, privacy concerns in Study I (*Intention to Donate Data*: $AME = -.06$, $p < .05$; *Participation in Data Donation*: $AME = -.03$, $p = .332$), correlated with only self-reported intentions but not actual participation. As such, the predictors of self-reported intentions to participate in data donation studies and actual participation behavior were similar.

Addressing Nonresponse Bias (RQ2a–c)

We tested a range of ex-ante error correction methods to address nonresponse bias. Based on Study I, we found that technical face-to-face support did not increase response rates (Figure 6, RQ2a). If anything, the response rates were highest without support (24%) compared to helping participants request (19%) or upload (16%) their data. Similarly, this ex-ante strategy did not decrease nonresponse bias ($bias_I$ = 8% for support during request, $bias_I$ = 12% for support during upload, $bias_I$ = 7% for the control group).

Similarly, providing personalized incentives did not increase the response rates (Figure 6, RQ2b). In Study I, the response rates were comparable for the participants who were offered an incentive (21%) and the control group (19%), which was similar to Study II (12% vs. 12%, respectively). We also found no shift in nonresponse bias in Study I ($bias_I$ = 8% in the experimental group, $bias_I$ = 8% in the control group) or Study II ($bias_{II}$ = 7% in the experimental group, $bias_{II}$ = 6% in the control group).

In Study II, we found that highlighting the societal relevance of donated data did not increase the response rates (Figure 6, RQ2c). The respondents to whom we explained the societal relevance of data donations were as likely to donate their data (12%) as the control group (12%). Similarly, nonresponse bias did not decrease due to our intervention ($bias_{II}$ = 6% in the control group, $bias_{II}$ = 6% in the experimental group).

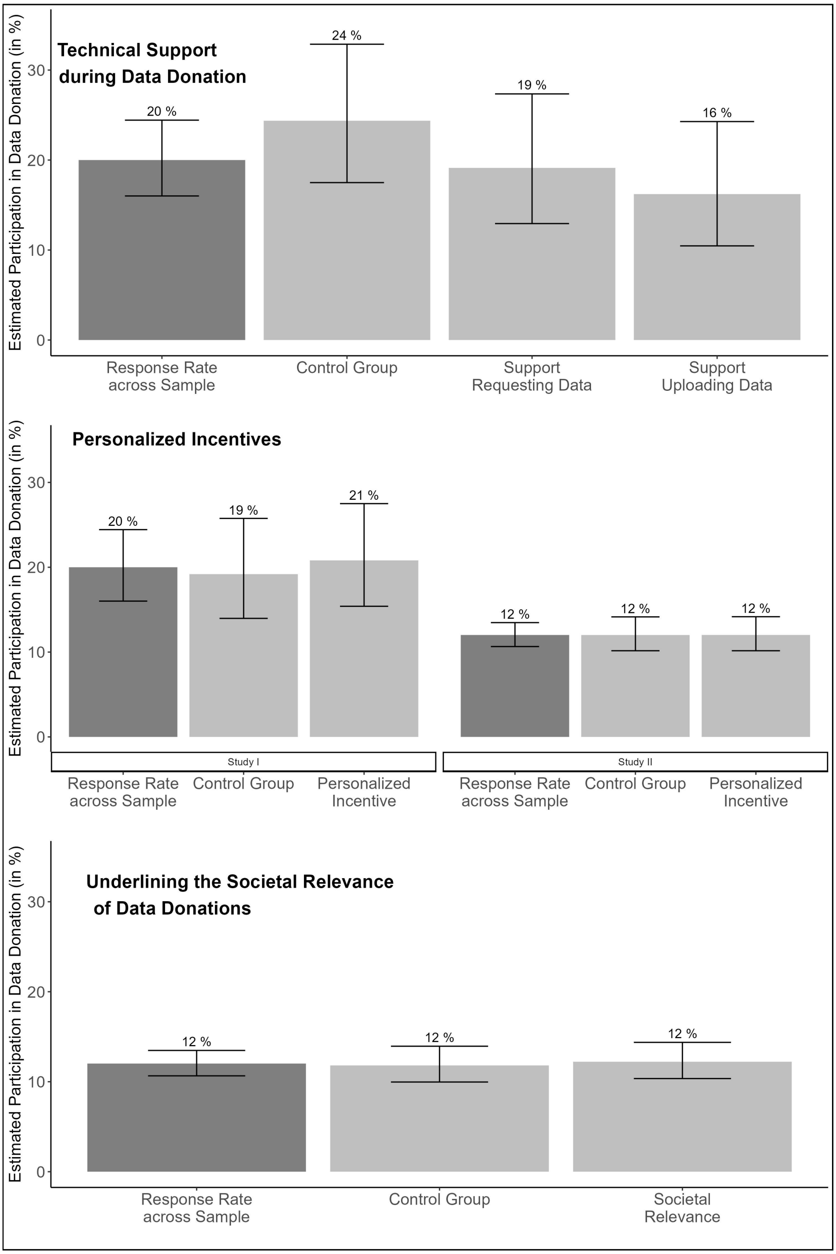

Figure 6: Effects of Ex-Ante Strategies.

Discussion

Can ex-ante error correction methods, here in the form of survey design strategies, mitigate sample-related bias in data donation studies? Using two experiments embedded in a data donation study, we show that the nonresponse rates and nonresponse bias are substantial in size—but that our ex-ante error approaches cannot mitigate either.

Quantifying Nonresponse Bias in Data Donation Studies

We identified high nonresponse rates and nonresponse bias in our data donation studies (RQ1). Overall, the self-reported intentions to donate data (63% Study I, 52% Study II) were around 40% higher than actual participation (20% Study I, 12% Study II). In addition to high nonresponse rates (see similarly Ohme et al., 2021; Silber et al., 2022), this indicates wide gaps between self-reported and actual behavior. Moreover, we found an average nonresponse bias of 7% for Study I and 6% for Study II, which was higher than the nonresponse bias found in, for example, sensor studies (Struminskaya et al., 2021). As indicated in prior research (Keusch et al., 2024; Ohme et al., 2021), politically interested and left-leaning respondents are more likely to provide digital traces, as are participants with lower privacy concerns, higher technical skills, or higher social media use. In contrast to the differences in the level of nonresponse rates, the predictors of nonresponse were relatively similar when comparing the participants' intentions to donate data and actual participation. Overall, we found that nonresponse rates and nonresponse bias may be a more pronounced problem for data donation studies than for studies that rely on data collection via tracking, linkage, or sensors.

In terms of nonresponse rates and nonresponse bias in data donation studies, this led to two conclusions. First, *researchers need to make transparent and quantify nonresponse rates and nonresponse bias.* This is especially important, as our results indicate that how people use digital media may be associated with whether they provide data, which indicates that nonresponse systematically correlates with dependent variables of interest. Respondents with higher technical skills or frequent social media use may find it easier to donate data. A worrisome reason for not donating data may be that participants consider it irrelevant, for instance, because they rarely use social media. Feedback from the interviewers involved in face-to-face recruitment and technical support in Study I provided anecdotal evidence of the latter: The respondents explained to the interviewers that they would not donate data from platforms because they never used them for news, which rendered their data "unimportant". If our goal were to study news engagement on social media, this could have led to biased estimates of such behavior based on digital traces. Second, given the differences in nonresponse rates and nonresponse bias, *researchers need to discuss and analyze whether knowledge about bias gained from linkage, tracking, or sensor studies can be transferred to the context of data donation*, as data collection processes may vary substantially.

Addressing Nonresponse Bias in Data Donation Studies

To mitigate nonresponse bias, we tested three ex-ante error correction methods: providing technical face-to-face support (RQ2a), offering personalized incentives (RQ2b), and underlining the societal relevance of data donations (RQ2c). None of these methods decreased the nonresponse rates or nonresponse bias, which could be due to two reasons. First, we may not have sufficiently decreased the expected burden or increased the expected rewards. For example, technical support (RQ2a) was mandatory. As the burden of providing data is a major obstacle to participation (Silber et al., 2022), the increased effort required by participants may explain the decreased response rates for this experimental factor. Second, the null effects for personalized incentives (RQ2b) and underlining the societal relevance of donations (RQ2c) in particular may point to a more general difficulty related to non-financial incentives: If these are offered at the beginning of studies, then delays of several days due to data take-outs may result in participants forgetting about incentives (for a similar argument, see Wenz & Keusch, 2023).

In terms of addressing nonresponse bias in data donation studies, we arrived at two conclusions. First, *researchers have to think of new ex-ante strategies to reduce the expected burden and increase the expected rewards*. Apart from financial incentives (Kmetty et al., 2024; Silber et al., 2022), our results are in line with those of existing studies, which have largely found limited or no effects of ex-ante strategies on providing data via linkage (Beuthner et al., 2024), sensors (Struminskaya et al., 2021), and data donation (Keusch et al., 2024; Kmetty et al., 2024). Related to this, a recent vignette experiment by Wenz and Keusch (2023) indicates that, in the context of tracking, participants' intentions to provide data are relatively stable across scenarios with different survey design strategies. As such, it seems that financial incentives are the most efficient and, to date, the only way to increase response rates through survey design (with, however, unclear effects on nonresponse bias). Because of these different nonresponse patterns, research cannot merely transfer error correction methods from survey research to the context of data donation. Moreover, we found that the most substantial nonresponse bias emerged related to variables other than sociodemographic characteristics, such as privacy- and technology-related attitudes and social media use. This casts doubt on whether a-posteriori error correction methods from survey research relying on such variables, such as weighting, can sufficiently address nonresponse bias in digital trace data (see similarly Jäckle et al., 2019; Pak et al., 2022). Consequently, *researchers need to adapt existing a-posteriori error correction methods by including substantial predictors of nonresponse beyond sociodemographic aspects.*

Limitations and the Road Ahead

Our study has several limitations. First, our findings are subject to measurement error, for example, due to platform-specific take-outs. Anecdotal evidence from the technical support sessions showed that the respondents were sometimes asked to send a copy of their national identification card to download data (Twitter), the DDPs had been deleted by platforms before the respondents could upload them (Instagram, Facebook), or the DDPs were empty because the respondents could use the platforms without being logged in (YouTube). The respondents also often used their smartphones to fill out the surveys. As they could not request or upload their data via their smartphones, this may have introduced further measurement-related bias. Consequently, future studies should extend our research on measurement-related bias related to data donation studies.

Second, our measures of nonresponse bias may include bias related to coverage, sampling, compliance, and consent. If the respondents downloaded data but (un)willingly missed uploading it, our measures of nonresponse bias may, for example, have been affected by compliance bias. Consequently, future studies could capture in more detail whether participants drop out when requesting, uploading, or deleting data, including which predictors explain dropout across these stages (see, for example, Gil-López et al., 2023). Similarly, we only quantified bias in means and variance—not how nonresponse bias may influence the size and direction of effects in the downstream inferential analysis (see critically Pak et al., 2022). Again, this would be an important avenue for future work.

Third, Study I is underpowered. Since we also tested experimental factors for RQ2b in Study II, this mostly affected the conclusions concerning technical support. Given that technical support had a reversed (though inconsistent) effect compared to what we expected, which is in line with recent studies published after our preregistration (Wenz & Keusch, 2023), it is unlikely that our null findings would have changed with a larger sample. However, it underscores that mandatory support is seen as an increasing survey burden. Due to limited resources for in-person support, we only tested this condition in the smaller student sample in Study I. This may have been problematic since this sample had slightly higher technical skills than the online access panel. This group may therefore have resisted the intervention because they deemed it unnecessary. Consequently, future studies could make support voluntary and could test other modes (e.g., support via chatbots) as means of developing ex-ante strategies to address bias in digital trace data.

Fourth, our findings cannot be generalized, as we relied on convenience samples and tested participation for specific platforms and metrics. Moreover, leverage-salience theory posits that individual perceptions of, for example, how interesting participants perceive incentives to be, vary (Groves et al., 2000). As such, survey design strategies may influence respondents to different degrees and have varying effects. We did not preregister and therefore test this, for instance, via interactions between respondent characteristics and survey design strategies (see similarly Struminskaya et al., 2021; Wenz & Keusch, 2023). Moreover, in the future, researchers could test responsive designs to motivate respondents who may otherwise be undersampled (e.g., by selectively offering support to those with lower technical skills).

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