1   Analyzing the Privacy Paradox Using a Nationally Representative Three-Wave Panel Study

Abstract

The privacy paradox states that people's concerns about online privacy are unrelated to their online sharing of personal information. On the basis of a representative sample of the German population, which includes 1403 respondents interviewed at three waves separated by 6 months, we investigate the privacy paradox from a longitudinal perspective. Using a cross-lagged panel model with random intercepts, we differentiate between-person relations from within-person effects. Results revealed that people who were more concerned about their online privacy than others also shared slightly less personal information and had substantially more negative attitudes toward information sharing (between-person level). People who were more concerned than usual also shared slightly less information than usual (within-person level). We found no long-term effects of privacy concerns on information sharing or attitudes 6 months later. The results provide further evidence against the privacy paradox, but more research is needed to better understand potential causal relations.

Keywords: privacy paradox, privacy concerns, information sharing, longitudinal analysis, structural equation modeling

Word count: 5053

19 Analyzing the Privacy Paradox Using a Nationally Representative Three-Wave Panel Study

20   The privacy paradox states that the information disclosure of Internet users is
21 problematic: Although many people are concerned about their privacy online, they still
22 share plenty of personal information on the web (e.g., Acquisti and Grossklags, 2003). The
23 privacy paradox is of considerable interest to society—it is discussed in newspapers (Frean,
24 2017), Wikipedia entries (Wikipedia, 2018), designated websites (New York Public Radio,
25 2018), books (Trepte and Reinecke, 2011), and top-tier academic journals (Acquisti et al.,
26 2015). If the privacy paradox really exists, it should inspire worry: It would suggest that
27 online behavior is irrational and that people are revealing too much of their personal
28 information, which can cause various problems (e.g., Sevignani, 2016). Understanding why
29 people disclose information online and whether or not this is paradoxical therefore
30 represents an important challenge.

31   However, current research on the privacy paradox has one major limitation. To the
32 best of our knowledge, most empirical studies conducted so far have investigated the
33 privacy paradox from a between-person perspective. By employing empirical tests of
34 relations between people (e.g., cross-sectional questionnaires analyzed with multiple
35 regression or Pearson correlations), studies have analyzed whether people who are more
36 concerned than *others* also share less personal information than *others*. Although such a
37 perspective is interesting and represents a viable first step, it cannot make informed claims
38 regarding causality. The privacy paradox, however, implies a causal perspective: Does a
39 person, if *he or she* becomes more concerned about online privacy, then also share less
40 personal information? This mismatch is problematic because although between-person
41 relations are, except for some special cases, a *necessary* condition for causal within-person
42 effects, they are by no means a *sufficient* one. For example, it could be that the
43 between-person relation is determined other third variables. Hence, as the next step in
44 investigating the privacy paradox and to better understand the causal relation between
45 privacy concerns and information sharing, it is necessary to conduct studies with

46 within-person designs.

47   With this study we aim to answer four major questions. First, on a between-person

48 level, how are concerns about online privacy related to the online sharing of personal

49 information? Second, on a within-person level, is information sharing lower than usual

50 when concerns are higher than usual? Third, what are the potential long-term effects? Are

51 changes in concerns related to changes in information sharing 6 months later and/or vice

52 versa? Fourth, what is the role of privacy attitudes, do they mediate the relation between

53 privacy concerns and information sharing? To best answer and contextualize these

54 questions, we first provide an in-depth theoretical analysis of the privacy paradox, after

55 which we present the empirical results of a longitudinal panel study, which is representative

56 of the German population.

A Brief History of the Privacy Paradox

57

58   Acquisti and Grossklags (2003) were among the first to argue that the online

59 disclosure of personal information is paradoxical. "Experiments reveal that very few

60 individuals actually take any action to protect their personal information, even when doing

61 so involves limited costs" (p.1). Three years later, Barnes (2006) discussed the behavior of

62 young people on SNSs, popularizing the term *privacy paradox*. Barnes listed six aspects of

63 online behavior that she considered to be particularly paradoxical: (a) illusion of privacy,

64 (b) high quantity of information sharing, (c) attitude behavior discrepancy, (d) lack of

65 privacy concerns, (e) lack of privacy literacy, and (f) fabrication of false information.

66 Norberg et al. (2007) were one of the first to empirically analyze the privacy paradox

67 explicitly. The study found a mismatch between concerns and behavior, which is aligned

68 with several other experimental studies conducted at the time (Beresford et al., 2012; Hann

69 et al., 2007; Huberman et al., 2005).

70   While there are various understandings and operationalizations of the privacy

71 paradox (Kokolakis, 2017), subsequent research focused on Barnes's third tenet, the

attitude-behavior discrepancy. Whereas some studies reported that privacy concerns were not significantly related to the disclosure of personal information (e.g., Gross and Acquisti, 2005; Taddicken, 2014; Tufekci, 2008), which lends credence to the privacy paradox, a different set of studies showed significant relations (e.g., Dienlin and Trepte, 2015; Heirman et al., 2013; Walrave et al., 2012), which refutes the privacy paradox.

Notably, in a parallel line of research other studies have also analyzed the relation between privacy concerns and information sharing. However, the term privacy paradox was often not used explicitly. Instead, studies have referred to the so-called *privacy calculus*, which states that the sharing of personal information online is affected by both the respective costs and the anticipated benefits (Culnan and Armstrong, 1999). By now, several studies have found empirical support for the privacy calculus in various online contexts (e.g., Bol et al., 2018; Dienlin and Metzger, 2016; Krasnova et al., 2010).

Baruh et al. (2017) published the first empirical meta-analysis on the relations between privacy concerns and various forms of social media use (e.g., information sharing or SNS usage). On the basis of 37 studies, Baruh et al. (2017) found a small and significant statistical relation between concerns about online privacy and online information sharing (r = -.13, 95% CI [-.07, -.18]). Another more recent meta analysis by Yu et al. (2020) also finds a significant bivariate relation between privacy concerns and information sharing, albeit smaller (r = -.06, 95% CI [-.01, -.12]). There also exist several systematic literature reviews on the privacy paradox (Barth and Jong, 2017; Gerber et al., 2018; Kokolakis, 2017). Kokolakis (2017) come to the conclusion that "the dichotomy between privacy attitude and behaviour should not be considered a paradox anymore." (p. 130) However, the authors also note that the privacy paradox is a "complex phenomenon that has not been fully explained yet". Barth and Jong (2017) are more skeptical, and argue that "attempts to theoretically explain and practically solve the problem of the privacy paradox are still scarce and we feel the subject deserves far more research attention" (p. 1052).

Defining Privacy Concerns and Information Sharing

Privacy is defined as the "[. . .] voluntary and temporary withdrawal of a person from the general society through physical or psychological means [. . .]" (Westin, 1967: 7). Privacy captures aspects of both volitional *control* and social *separateness* (Bräunlich et al., 2020; Marwick and boyd, 2014). People from all cultural backgrounds require privacy to fulfill fundamental needs including personal care, protected communication, intimacy, or sexuality (Altman, 1977; Westin, 1967). Being a universal human right (UN General Assembly, 1948, Art. 12), privacy is essential for safety, psychosocial flourishing, and dignity. It is driven by both individual needs and interpersonal negotiations thereof (Trepte, 2020).

Several dimensions of privacy have been proposed. For example, it is possible to distinguish a vertical and a horizontal level (Masur, 2018). Whereas the vertical level captures privacy from authorities, institutions, or companies, horizontal privacy addresses privacy from peers, colleagues, or other people. When it comes to concerns in general, interestingly they do not seem to be established as a stand-alone theoretical concept in psychology (Colman, 2015). Concerns are usually understood as an uneasy mix of "interest, uncertainty, and apprehension" (Merriam-Webster, 2018). As a theoretical construct, privacy concerns can hence be categorized as an affective motivational disposition. Taken together, concerns about online privacy represent how much an individual is motivated to focus on his or her control over a voluntary withdrawal from other people or societal institutions on the Internet, accompanied by an uneasy feeling that his or her privacy might be threatened.

The online sharing of personal information, on the other hand, captures how much person-related information people share when they use the Internet. Information sharing can be differentiated from communication and self-disclosure. Communication is broad, because it comprises all verbal and nonverbal information that is emitted (e.g., Watzlawick et al., 2011). Self-disclosure is more narrow, because it focuses on deliberate revelations

about the true self to others, which including aspects such as personal fears, values, or plans (e.g., Jourard, 1964). Information sharing is even more specific, because it addresses only person-related information, including information about their age, sex, name, address, health, and finances.

In what follows we hence investigate the two concepts of (a) concerns about online privacy and (b) online information sharing, aiming to investigate how they relate conceptually. In doing so, we adopt and focus on the perspective of individual people.

The Relation Between Privacy Concerns and Information Sharing

Currently, there is a lack of studies that explicitly analyze how behavior is affected by *concerns* in general. Fortunately, however, we know much about the behavioral effects of related concepts such as attitudes or fears, which all can affect behavior, sometimes profoundly (Fishbein and Ajzen, 2010; Rogers, 1983). Emotions, perhaps the concept most closely related to concerns, have a particularly strong effect on behavior. By causing fight, flight, or freeze reactions, they are a primordial trigger of behavior and are considered to be an adaptive mechanism of evolved species (Dolan, 2002).

Also empirically, concerns have been shown to affect behavior (Hayes and Ross, 1987; Reel et al., 2007). For example, people more concerned about the environment show more environment-related behaviors (Bamberg, 2003). Taken together, it is reasonable to expect that also concerns about online privacy should somehow reflect in the online sharing of personal information.

At the same time, there are some factors that likely diminish the relation. Most prominently, there is the so-called *attitude behavior gap* (Fishbein and Ajzen, 2010), which states that people sometimes act against their own attitudes. Evidently, not everyone concerned about their physical health exercises regularly. The explanation is simple: Other factors such as subjective norms and perceived behavioral control also determine behavior (Ajzen, 1985), which automatically reduces the impact of attitudes or concerns.

151   Specifically, two of the most influential factors that affect online information sharing

152 are (a) strong subjective norms (Heirman et al., 2013) and (b) expected benefits (Krasnova

153 et al., 2010). In other words, users often prioritize social support, special offers, or

154 improved services, accepting that their privacy will be diminished. Sometimes, privacy

155 concerns do not relate information sharing, because users lack the skills, knowledge, or

156 literacy to change their online behavior, creating feelings of apathy or cynicism (Hargittai

157 and Marwick, 2016; Hoffmann et al., 2016). Likewise, personal information is also often

158 shared by others, a phenomenon described as "networked privacy" (Marwick and boyd,

159 2014), which further reduces the power of individuals to determine how much personal

160 information can be found online. Trepte et al. (2014) listed several factors that can

161 additionally attenuate the relation: lack of strength of concerns, absence of negative

162 personal experiences, or situational constraints due to social desirability. In conclusion,

163 also in the context of the privacy paradox it *not* reasonable to expect a *perfect* relation

164 between attitudes and behaviors. However, we should still expect to find a relation that is

165 *small* or *moderate.*

166   There are also some methodological explanations as to why some studies did not

167 detect statistically significant relations. Researchers are always confronted with the

168 so-called *Duhem-Quine problem*, according to which it is impossible to test theories in

169 isolation, because empirical tests always rely on auxiliary assumptions (Dienes, 2008). In

170 other words, if a psychological experiment fails, we do not know whether the theory is

171 wrong or the questionnaire subpar. This tenet is particularly relevant for the privacy

172 paradox: Detecting statistical significance for small effects—and, again, we should expect

173 to find small effects—is more challenging because it means that large samples are necessary

174 to guarantee sufficient statistical power.[1] Precisely, in order to be capable of detecting a

175 correlation between privacy concerns and information sharing in 95% of all cases, which

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[1] Statistical power describes the probability of statistically detecting an effect that exists empirically. Only with high statistical power is it possible to make valid claims about an effect's existence (Cohen, 1992).

Baruh et al. (2017) estimated to be r = -.13, we need a sample of N = 762 people. The

reality, however, looks different: In their meta-analysis, Baruh et al. (2017) reported a

median sample size of N = 300, which can explain why several studies did not find

significant effects.

In conclusion, we expect to find a small significant relation between privacy concerns

and information sharing, both on the between-person level (Hypothesis 1) and the

within-person level (Hypothesis 2).[2]

Hypothesis 1: People who are more concerned about their online privacy than others

will also be less likely to share personal information online than others.

Hypothesis 2: People who are more concerned about their online privacy than they

usually are will also share less personal information online than they usually do.

Long-Term Perspective

Although short-term effects are likely, it is still unclear whether long-term effects

exist as well. First, when analyzing potential long-term effects, it is important to choose an

interval that is both plausible and relevant. (It makes a large difference whether the effects

of alcohol consumption on driving performance are tested after say 1 minute, 1 hour, or 1

day.) One factor that determines an interval's optimal length is the stability of the

variables (Dormann and Griffin, 2015). Privacy concerns and privacy attitudes are

predominantly trait-like constructs with high stabilities, which is why they necessitate

longer intervals. Other studies with comparable research questions have therefore used an

interval of 6 months (e.g., Valkenburg and Peter, 2009), which we adopt also in this study.

In general, we believe that it should be possible to find long-term effects. It has been

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[2] To explain, with Hypothesis 1, we compare *different* people with one another by analyzing their *average* values across all measurements. In other words, does a person, who is generally more concerned than others, also generally share less information than others? With Hypothesis 2, we compare *specific* measurements within the *same* person. In other words, does a person, if he/she is more concerned on T1 than on average, share more or less information on T1 than on average?

argued that privacy concerns affect privacy behavior in the long run (e.g., Heirman et al., 2013). The underlying theoretical mechanism could be that the emotional part of privacy concerns causes (a) motivated information selection and (b) motivated information processing, which is likely to change actual behavior (Nabi, 1999). Specifically, when privacy concerns are higher than usual (e.g., because of experienced or witnessed privacy infringements), people might begin reading more media articles on privacy issues and might also consume these articles more carefully, which could prompt information sharing practices that are more cautious. Also empirically, a study with 290 participants found small negative longitudinal (between-person) relations between privacy concerns and self-disclosure (Koohikamali et al., 2019).

At the same time, the adverse effect seems plausible as well, with two potential outcomes. On the one hand, the long-term relation could be positive: If people start to share more information online, they might become increasingly aware that their privacy is at risk, thereby stirring concern (Tsay-Vogel et al., 2018). On the other hand, the long-term relation might also be negative: When people share more personal information online they might become accustomed to doing so, which potentially reduces concern (for example, due to the mere exposure effect; Zajonc, 1968). Finally, there could also be no long-term relation at all: People might have already become used to sharing information online, which stifles further cognitive or emotional processing. This rationale is central to *privacy cynicism* (e.g., Hoffmann et al., 2016).

Research Question 1.1: Do changes in concerns about online privacy affect the online sharing of personal information 6 months later?

Research Question 1.2: Do changes in the online sharing of personal information affect concerns about online privacy 6 months later?

The Role of Attitudes

It has been argued that privacy attitudes could bridge the gap between concerns and information sharing (e.g., Dienlin and Trepte, 2015). In contrast to privacy concerns, privacy attitudes capture a more explicit, fluctuating cognitive appraisal (Tsay-Vogel et al., 2018). Although both variables are related to information disclosure, attitudes are likely the better predictor. This reasoning follows the rational choice paradigm (Simon, 1955), which maintains that behavior is always at least partially influenced by convictions, attitudes, and cost-benefit analyses. Also empirically, a study of 1,042 youths from Belgium found that the relation between privacy attitudes and disclosure of personal information was strong ($r = .56$), whereas the relation between privacy concerns and disclosure was only moderate ($r = -.29$; Heirman et al., 2013).

Hypothesis 3.1: People who are more concerned about their online privacy than others will also hold a less positive attitude toward the online sharing of personal information than others.

Hypothesis 3.2: People with a more positive attitude toward the online sharing of personal information than others will also share more information online than others.

Hypothesis 4.1: People who are more concerned about their online privacy than they usually are will also hold a less positive attitude toward the online sharing of personal information than they usually do.

Hypothesis 4.2: People with a more positive attitude toward the online sharing of personal information than they usually have will also share more information online than they usually do.

Concerning the potential long-term relations of privacy attitudes, we are confronted with the same situation mentioned above. Because we are not aware of research on long-term relations, several scenarios seem plausible. Attitudes could either have long-term relations or not, and information sharing could either foster privacy attitudes or diminish them.

249   Research Question 2.1: Do changes in concerns about online privacy affect attitudes

250 toward the online sharing of personal information 6 months later?

251   Research Question 2.2: Do changes in attitudes toward the online sharing of personal

252 information affect concerns about online privacy 6 months later?

253   Research Question 3.1: Do changes in attitudes toward the online sharing of personal

254 information affect the online sharing of personal information 6 months later?

255   Research Question 3.2: Do changes in the online sharing of personal information

256 affect attitudes toward the online sharing of personal information 6 months later?

257   **Method**

Procedure and Respondents

259   This study is part of a large-scale project which investigates the development of

260 privacy and self-disclosure, including several other variables. Other publications linked to

261 the project can be accessed at [link blinded during review]. The data come from a

262 longitudinal paper-and-pencil questionnaire study, in which a representative sample of the

263 German population (16 years and older) was surveyed on overall five occasions. The data

264 can be downloaded from [link blinded during review].

265   The first three waves were collected from May 2014 to May 2015, with intervals of 6

266 months each. The last two waves were collected on May 2016 and May 2017, and had an

267 interval of one year. Because we hypothesized the effects to take place across half a year,

268 the last two waves were not included in the analyses presented here. First, a sample of

269 14,714 potential respondents was drawn from a representative omnibus survey in Germany

270 (ADM master sample), using a random last-two-digit dialing procedure. In this CATI

271 screening, 5,286 respondents agreed to participate in all following waves. Wave 1 was

272 completed by 3,278 respondents (response rate: 38%), Wave 2 by 2,448 respondents

273 (attrition rate: 25%), and Wave 3 by 2,021 respondents (attrition rate: 17%). We filtered

274 respondents who never used the Internet at all waves, answered fewer than 50% of the

275 items in each scale for at least one wave, provided inconsistent birth-dates across

276 measurements, or did not report sociodemographic variables. The final sample consisted of

277 $n = 1{,}403$ respondents.

278   In the final sample, the rate of missing data was 5.40%. Visual inspection of the

279 missing value patterns as well as the non-parametric test by Jamshidian et al. (2014)

280 suggested that all missing values could be considered missing at random ($p = .514$).

281 Therefore, Full Information Maximum Likelihood estimation was conducted using all

282 available data. The average age was 54 years ($SD = 15$ years), and 49% were male. About

283 39% reported that they had graduated from college.

Measures

285   We tested the factorial validity of all measures using confirmatory factor analysis

286 (CFA). Each CFA included the items from all three waves. For each item, factor loadings

287 were constrained to be equal across waves. Constrained and unconstrained models were

288 compared using χ^2 differences tests. All results were nonsignificant, suggesting longitudinal

289 factorial invariance. The measures showed good composite reliability in all three waves.

290 Graphical displays of the variables' distributions showed that privacy concerns were skewed

291 to the left, privacy attitudes were normally distributed, and information sharing was

292 skewed to the right (Figure 2, diagonal). We calculated intra-class correlation coefficients

293 to quantify how much variance in the variables' factor scores could be attributed to

294 between-person differences. An English translation of the original German items can be

295 found in the OSM.

296   **Concerns about online privacy.**   Privacy concerns were measured as a

297 second-order factor. Three self-developed items captured the vertical dimension (e.g., "How

298 concerned are you that institutions or intelligence services collect and analyze data that

299 you disclosed on the Internet?"), and three items by Buchanan et al. (2007) captured the

300 horizontal dimension (e.g., "How concerned are you that people that you do not know

might obtain information about you because of you online activities?"). Respondents rated

all items on a 5-point scale ranging from 1 (*not at all concerned*) to 5 (*very concerned*).

The means were $M_{t1} = 3.67$, $M_{t2} = 3.62$, $M_{t3} = 3.59$, and the standard deviations $SD_{t1} =$

0.88, $SD_{t2} = 0.89$, and $SD_{t3} = 0.90$. The two-dimensional model fit the data well, $\chi^2(118)$

$= 661.17$, $p < .001$, cfi $= .97$, rmsea $= .06$, 90% CI [.05, .06], srmr $= .04$. The reliability

was high ($\omega_{t1} = .95$, $\omega_{t2} = .96$, $\omega_{t3} = .97$). Overall, 73.85% of the measure's variance was

explained by differences between persons.

The online sharing of personal information. To measure respondent's level of

information disclosure, they were asked how often they disclosed 10 different pieces of

information on the Internet (European Commission, 2011). The exact question was: "How

often do you disclose the following pieces of information online (i.e., on the Internet)?"

Each item was answered on a 5-point scale ranging from 1 (*never*) to 5 (*daily*). Factor

analyses suggested a second-order factor structure with five first-order factors of two items

each. The first first-order factor subsumed financial and medical information, the second

first and last name, the third place of residence and street (including house number), the

fourth email address and phone number, and the fifth information about education and

current job. The means were $M_{t1} = 2.12$, $M_{t2} = 2.13$, $M_{t3} = 2.10$, and the standard

deviations $SD_{t1} = 0.66$, $SD_{t2} = 0.64$, and $SD_{t3} = 0.61$. The model fit the data adequately,

$\chi^2(375) = 2527.69$, $p < .001$, cfi $= .95$, rmsea $= .06$, 90% CI [.06, .07], srmr $= .06$. The

reliability was high ($\omega_{t1} = .91$, $\omega_{t2} = .92$, $\omega_{t3} = .91$). Overall, 64.29% of the measure's

variance was explained by differences between persons.

Attitudes toward the online sharing of personal information. Respondents'

attitudes toward disclosing personal information online were captured with 10 items that

measured the general appraisal of disclosing the same 10 pieces of information (European

Commission, 2011). Adhering to the principle of compatibility (Fishbein and Ajzen, 2010),

the items were parallel to those of the actual disclosure scale. Specifically, we asked: "Do

you think that it is sensible to disclose the following pieces of information online (i.e., on

the Internet)?" The scale ranged from 1 (*not at all sensible*) to 5 (*very sensible*). The

means were $M_{t1} = 3.67$, $M_{t2} = 3.62$, $M_{t3} = 3.59$, and the standard deviations $SD_{t1} = 0.88$,

$SD_{t2} = 0.89$, and $SD_{t3} = 0.90$. The second-order model with five first-order factors showed

an adequate model fit, $\chi^2(375) = 2683.43$, $p < .001$, cfi = .93, rmsea = .07, 90% CI [.06,

.07], srmr = .08. The reliability was high ($\omega_{t1} = .88$, $\omega_{t2} = .89$, $\omega_{t3} = .87$). Overall, 59.19%

of the measure's variance was explained by differences between persons.

Data Analysis

We follow the recommendation by Lakens, Adolfi, et al. (2018) and first justify the

choice of our alpha level. We determined adequate error margins by considering the

potential implications of both false positive and false negative findings (i.e., alpha and beta

errors): On the one hand, if we committed an alpha error, we would wrongfully conclude

that people's concerns and behaviors are consistent. Communicating such a false result to

the public might unjustly reassure people when they should be more alert. On the other

hand, if we committed a beta error, we would wrongfully conclude that individuals behave

paradoxically. Communicating such a false result would unjustly accuse people of

implausible behavior, potentially causing unnecessary distress or reactance. We consider

both errors to be equally detrimental. Hence, we chose balanced error rates, setting a

maximum error rate of 5% for both alpha and beta. As the smallest effect size of interest

(SESOI; Lakens, Scheel, et al., 2018), we chose to consider effects that are at least small

(i.e., standardized coefficients above $\beta = .10$; Cohen, 1992) as able to offer empirical

support for our theoretical hypotheses. Significantly smaller effects were not considered

able to offer support. The six hypotheses were tested with a one-tailed approach and the

six research questions with a two-tailed approach. On the basis of the balanced alpha-beta

approach with a maximum error probability of 5%, a desired power of 95%, and an SESOI

of $\beta = .10$, we calculated a minimum sample size of 1,293 respondents. Given the final

sample size of 1,403 respondents, alpha and beta errors were balanced for our hypotheses

354 (research questions) when we used a critical alpha of 3% (4.20%), resulting in a power of

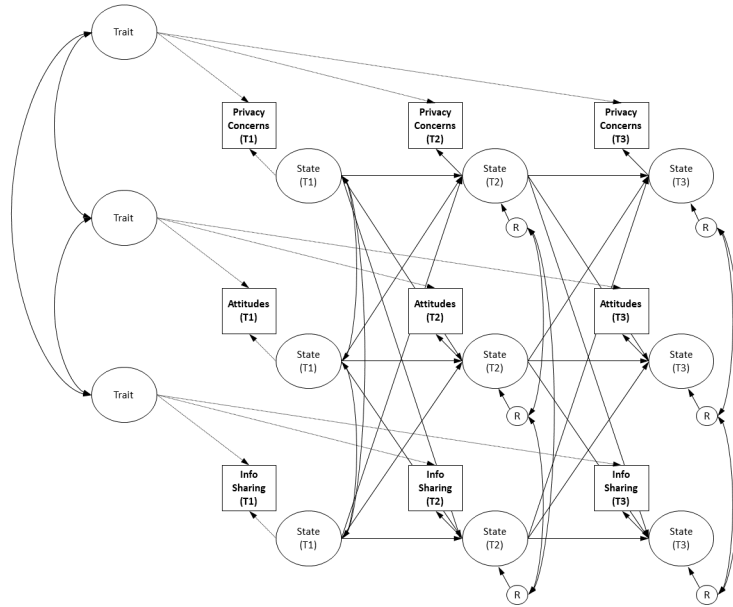355 97% (95.80%) to detect small effects.

Figure 1. Visual representation of the estimated random-intercept cross-lagged panel model
(RI-CLPM).

356   The data were analyzed using of a random-intercept cross-lagged panel model

357 (RI-CLPM, Hamaker et al., 2015). For a visualization, see Figure 1. Note that in contrast

358 to regular cross-lagged panel models (CLPMs), RI-CLPMs can separate between-person

359 variance from within-person variance. We used factor scores as observed variables to

360 represent the variables' latent structure more closely. We tested H1, H3.1, and H3.2 by

361 correlating the random intercepts, which represent the respondents' individual mean scores

362 across all three waves. We tested H2, H4.1, and H4.2 by correlating the respondents'

363 within-person variance at T1, which captures their specific deviation at T1 from their

364 overall score. We tested all research questions by regressing variables on all other measures

365 obtained 6 months earlier. Given that we had three points of measurement, this resulted in

366 two estimates for each research question. As we did not assume longitudinal effects to

367 differ across time, they were constrained to be equal across all waves, which produces one

single general measure of each effect instead of two time-specific ones. (We later tested this assumption empirically. As expected, the model with constrained effects did not show significantly reduced model fit, $\chi^2(9) = .114$, $p = 14.25$, which supports that effects did not change over time.) Fit was assessed according to the common criteria as described by Kline (2016). The final model fit the data well, $\chi^2(15) = 25.18$, $p = .048$, cfi $= 1.00$, rmsea $= .02$, 90% CI [$< .01$, $.04$], srmr $= .01$.

For the analyses, we used R (Version 4.0.3; R Core Team, 2018) and the R-packages *GGally* (Version 2.0.0; Schloerke et al., 2018), *ggplot2* (Version 3.3.2; Wickham, 2016), *lavaan* (Version 0.6.7; Rosseel, 2012), *MissMech* (Version 1.0.2; Jamshidian et al., 2014), *MVN* (Version 5.8; Korkmaz et al., 2014), *psych* (Version 2.0.9; Revelle, 2018), *pwr* (Version 1.3.0; Champely, 2018), *semTools* (Version 0.5.3; Jorgensen et al., 2018), and *sjstats* (Version 0.18.0; Lüdecke, 2019). The code, additional analyses, and a reproducible version of this manuscript can be found on the manuscript's companion website at https://xmtra.github.io/privacy-paradox.

Results

In a first descriptive step, we analyzed the variables' bivariate relations. All variables associated with the hypotheses showed correlations that were in line with our theoretical rationales (Figure 2, above the diagonal).

Hypothesis 1 predicted that people reporting higher concerns about online privacy than others would also be less likely to share personal information online than others. Results revealed that the random intercepts of the two variables were significantly correlated ($\beta = -.09$, $b = -0.03$, 95% CI [-0.05, -0.01], $z = -2.57$, $p = .005$). Hence, respondents who—on average across all three waves—were more concerned about their privacy than others also shared slightly less personal information online. The effect was small. When looking at the standardized effect's confidence interval (i.e., $\beta = -.09$, 95% CI [-.15, -.02]), it was not significantly smaller than our SESOI of *beta* $= .10$. Thus,
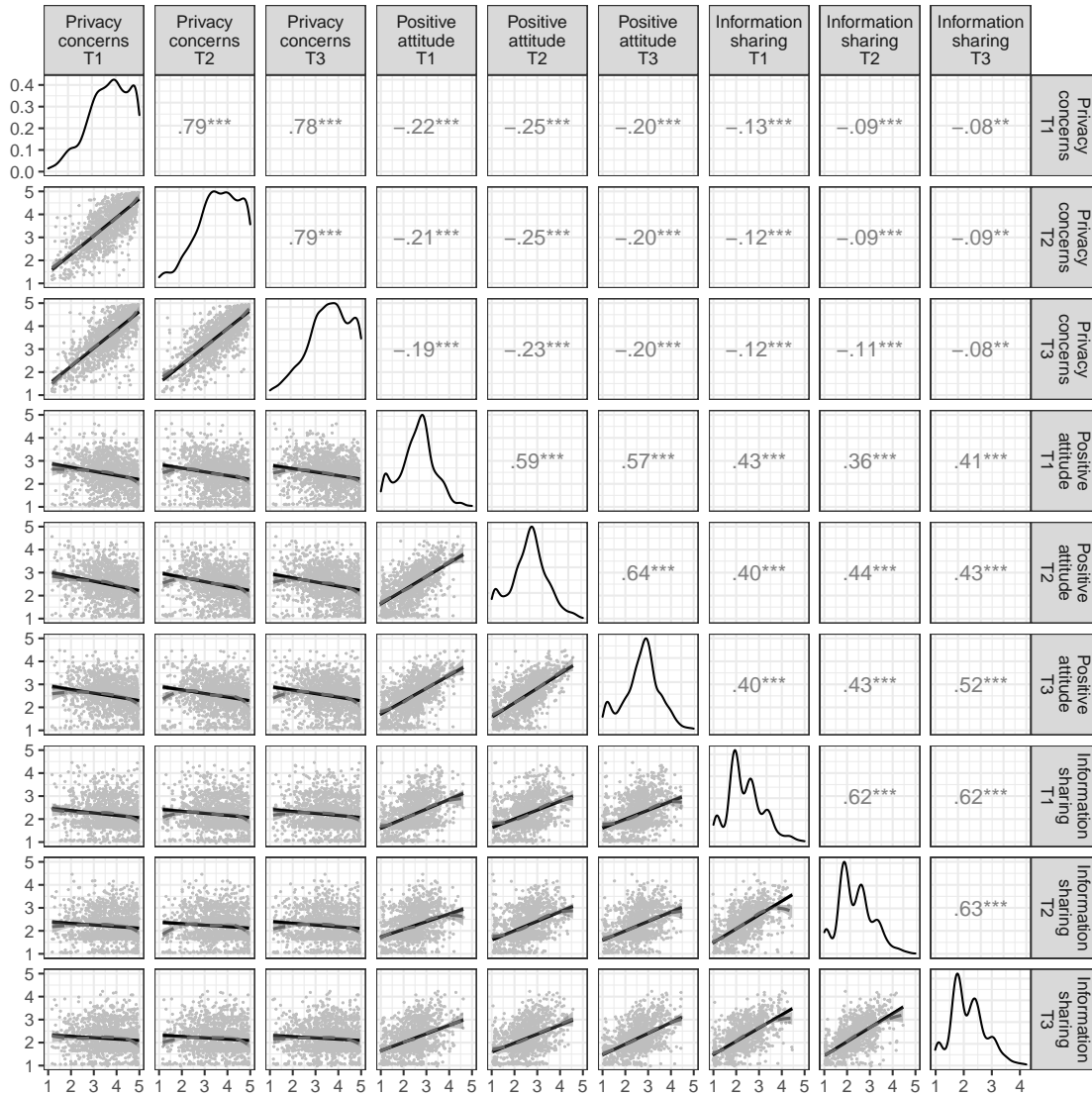
Figure 2. Results of the bivariate relations. Above the diagonal: zero-order correlation matrix; diagonal: density plots for each variable; below the diagonal: bivariate scatter plots for zero-order correlations. Solid regression lines represent linear regressions, dashed regression lines represent quadratic regressions. Calculated with the variables' latent factor scores.

394 Hypothesis 1 was supported.

395   Hypothesis 2 proposed that if people perceived more concerns about their online

396 privacy than they usually do, they would also share less personal information online than

they usually do. Results revealed a small significant correlation (β = -.10, b = -0.02, 95%

CI [-0.03, > -0.01], z = -2.37, p = .009), suggesting that if respondents were more

concerned about their online privacy at T1 than usual, they also shared less personal

information online at T1 than usual. In conclusion, the results supported Hypothesis 2.

With Research Question 1.1, we analyzed the longitudinal relation of concerns about

online privacy and the online sharing of personal information 6 months later. No significant

lagged effect across 6 months was found (β = .01, b = 0.01, 95% CI [-0.05, 0.07], z = 0.41,

p = .683). With Research Question 1.2, we investigated the longitudinal relation of the

online sharing of personal information and concerns about online privacy 6 months later,

again revealing no significant effect (β = -.03, b = -0.03, 95% CI [-0.09, 0.04], z = -0.80, p

= .422).

Hypothesis 3.1 predicted that people who perceived more privacy concerns than

others would also hold more negative attitudes toward the online sharing of personal

information than others. The results revealed a medium-sized negative correlation between

the two variables on the between-person level (β = -.31, b = -0.11, 95% CI [-0.14, -0.08], z

= -8.46, p < .001). Thus, people who—on average across all three waves—reported being

more concerned about their online privacy relative to the rest of the sample, were also

substantially more likely to hold a more negative attitude toward the online sharing of

personal information. The results therefore supported Hypothesis 3.1. Hypothesis 3.2

stated that people who held more positive attitudes toward the online sharing of personal

information than others would also share more personal information online than others.

Results showed a very strong between-person correlation between the two variables (β =

.66, b = 0.15, 95% CI [0.13, 0.17], z = 15.12, p < .001). In other words, when averaged

across all three waves, if people had more positive attitudes toward the online sharing of

personal information than others, they were much more likely to actually share personal

information online. In conclusion, the results supported Hypothesis 3.2.

Hypothesis 4.1 proposed that people who perceived more privacy concerns than usual

424 would also hold more negative attitudes toward the online sharing of personal information

425 than usual. The results did not reveal a significant effect (β = -.06, b = -0.01, 95% CI

426 [-0.03, < 0.01], z = -1.38, p = .084). Hypothesis 4.2 proposed that people who held more

427 positive attitudes toward the online sharing of personal information than usual would also

428 share more personal information online than usual. Results showed a moderate

429 within-person correlation between the two variables (β = .15, b = 0.03, 95% CI [0.02, 0.05],

430 z = 4.01, p < .001), which indicates that when respondents had more positive attitudes at

431 T1 than usual, they also shared more personal information than usual. In conclusion, the

432 results supported Hypothesis 4.2.

433   With Research Question 2.1, we analyzed the longitudinal relations of concerns about

434 online privacy and positive attitudes toward the online sharing of personal information. No

435 significant effect was found (β = -.02, b = -0.02, 95% CI [-0.09, 0.06], z = -0.47, p = .641).

436 Regarding Research Question 2.2, again no significant longitudinal relations emerged

437 between privacy attitudes and privacy concerns 6 months later (β < .01, b < 0.01, 95% CI

438 [-0.06, 0.06], z = 0.06, p = .951).

439   Research Question 3.1 asked whether changes in attitudes toward the online sharing

440 of personal information would affect changes in personal information sharing 6 months

441 later. No significant effect was found (β > -.01, b > -0.01, 95% CI [-0.06, 0.05], z = -0.07, p

442 = .947). Next, Research Question 3.2 asked whether changes in the online sharing of

443 personal information would affect attitudes toward the online sharing of personal

444 information 6 months later. Again, no significant effect was found (β = .04, b = 0.04, 95%

445 CI [-0.03, 0.11], z = 1.15, p = .249).

446   Table 1 presents an overview of all results.

447   In an additional analysis, we also tested the same model with a 1 year interval, which

448 allowed to include data spanning until winter 2016 and 2017. Most effects remained the

449 same. For example, we again found that people more concerned than others were less

450 positive regarding information sharing (r = -.36, p < .001) and shared less information (r

Table 1

Parameter Estimates Obtained in the Random-Intercept Cross-Lagged Panel Model

Effect	b	95% CI		beta	p
		ll	ul		
Between-person correlations across all waves					
Privacy concern <-> information sharing	-0.03	-0.05	-0.01	-.09	.005
Privacy concern <-> positive attitude	-0.11	-0.14	-0.08	-.31	< .001
Positive attitude <-> information sharing	0.15	0.13	0.17	.66	< .001
Within-person correlations at T1					
Privacy concern <-> information sharing	-0.02	-0.03	> -0.01	-.10	.009
Privacy concern <-> positive attitude	-0.01	-0.03	< 0.01	-.06	.084
Positive attitude <-> information sharing	0.03	0.02	0.05	.15	< .001
Within-person effects across 6 months					
Privacy concern -> information sharing	0.01	-0.05	0.07	.01	.683
Information sharing -> privacy concern	-0.03	-0.09	0.04	-.03	.422
Privacy concern -> positive attitude	-0.02	-0.09	0.06	-.02	.641
Positive attitude -> privacy concern	< 0.01	-0.06	0.06	< .01	.951
Positive attitude -> information sharing	> -0.01	-0.06	0.05	> -.01	.947
Information sharing -> positive attitude	0.04	-0.03	0.11	.04	.249

Note. The between-person correlations represent interpersonal relations. For example, results showed that people who were more concerned than others, averaged across all three waves, also shared less information than others. The within-person parameters reflect how intrapersonal changes in one variable are related to intra-personal changes in another. For example, results showed that if a person was more concerned at T1 than usual, they also shared less information than usual.

451   = -.15, p = .002). Likewise, people more positive toward data sharing than others also

452   shared substantially more data (r = .66, p < .001). Because including these two additional

453   waves significantly reduces sample size, and because we consider it more likely that effects

454   take place more immediately, these results should be considered exploratory. For an

455   overview of the results, see the additional analyses on our companion website (Section

456   2.1.2.7).

Discussion

458   Most research on the privacy paradox suggests a significant small effect of privacy

459   concerns on the online sharing of personal information (e.g., Baruh et al., 2017). However,

460   whereas the theoretical premise of the privacy paradox addresses a within-person *effect*,

461   most empirical studies have analyzed only between-person *relations*. On the basis of a

462   representative sample of the German population, from which three waves of data separated

463   by 6 months were collected, we hence analyzed the privacy paradox by differentiating

464   general between-person relations, short-term within-person relations, as well as long-term

465   within-person effects. Together, this approach allows for informed inferences about the

466   variables' causal relationship.

467   The results of the between-person analyses showed that people who were more

468   concerned about their privacy than others were slightly less likely to share personal

469   information. In addition, people who were more concerned about their privacy than others

470   also held substantially more negative attitudes toward disclosing personal information

471   online. Notably, we found a very strong between-person correlation between attitudes

472   toward information sharing and actual information sharing, which shows that typical

473   online disclosure can be predicted precisely by a person's attitude. Taken together, the

474   cross-sectional results are in line with the extant literature: The between-person correlation

475   of privacy concerns and information sharing found in this study (i.e., β = -.09) fall within

476   the 95% confidence interval of the effect reported by Baruh et al. (2017) (i.e., r = -.13,

477 95% CI [-.07, -.18]). Notably, the between-person correlations reported here represent

478 averaged measurements across three waves, which makes the findings more robust than

479 typical one-shot measures.

480   In conclusion, this study suggests that the privacy paradox does not exist on a

481 between-person level. The differences between people with regard to their online

482 information sharing behavior can be explained by differences in their privacy concerns to a

483 small extent, and by differences in their privacy attitudes to a large extent. The more

484 specific we become, the better we can explain online behavior: Whereas privacy concerns

485 are related only weakly to online information sharing (e.g., Baruh et al., 2017), more

486 specific risks perceptions are related to behavior more closely (e.g., Bol et al., 2018; Yu et

487 al., 2020), whereas behavioral attitudes are the best predictors (Dienlin and Trepte, 2015).

488   The within-person results showed that when a person's privacy concerns are higher

489 than usual, the same person also shared slightly less information online than usual.

490 Moreover, people who developed more positive attitudes toward the online sharing of

491 personal information than usual, also shared substantially more personal information

492 online. Together, changes in concerns and attitudes are therefore related to changes in

493 behavior, which speaks against the privacy paradox also on the within-person level.

494   We did not find any long-term effects, however. Changes in both privacy concerns

495 and attitudes toward the online sharing of personal information were not related to any

496 meaningful changes in the online sharing of personal information 6 months later (and vice

497 versa). As an explanation, it might be the case that changes in privacy concern affect

498 information sharing more immediately. To test this assumption, we would need studies

499 with shorter intervals (Keijsers, 2016). Moreover, given that the directions of most

500 longitudinal relations were in line with the between-person and within-person relations,

501 longitudinal effects might indeed take place, but only that they are very small. Of course,

502 it could also be that longterm longitudinal effects do not exist.

Limitations

The data were collected between May 2014 and May 2015—hence, after the Snowden revelations in 2013, but before the Equifax data breach in 2017, the Cambridge Analytica data breach in 2018, or the implementation of the General Data Protection Regulation in 2018. Such sweeping events, however, could affect privacy concerns, online behavior, or their mutual relation, which would limit the generalizability of our results. Although this is an important caveat, we have reason to believe that our findings are largely robust. First, additional analyses showed that the within-person relationships were stable across waves (a period of 1 year). Second, another set of additional analyses showed that most effects remained stable until winter 2017. Third, records of online search terms revealed that although interest in privacy-related topics and privacy-enhancing technologies increased after the Snowden revelations, it returned to prior levels after only two weeks (Preibusch, 2015). It thus seems that levels of privacy concerns and information sharing, as well as their mutual relationship, are largely robust.

In asking how much information respondents share when using the Internet in general, we automatically aggregated different platforms, contexts, and situations. However, privacy mechanisms can differ largely across contexts (Nissenbaum, 2010) and situations (Masur, 2018). Our broad perspective, therefore, is somewhat problematic and limits our capacity to understand and predict the behavior of individual people in specific situations. At the same time, aiming to maximize generalizability, we were able to extract some general underlying patterns, which can serve as a starting point for more contextualized analyses (see below).

Some of the effect sizes reported in this study are potentially not large enough to refute the privacy paradox completely. On the one hand, they could be a manifestation of the so-called "crud factor" (Meehl, 1990: 204), which states that all psychosocial measures are related to one another to some extent. On the other hand, additional factors such as expected benefits might play a more important role (Dienlin and Metzger, 2016). In

conclusion, although our results suggest that privacy concerns and privacy attitudes are correlated with information sharing, the importance of privacy concerns should not be exaggerated. The effects could be larger, and other variables play a role as well.

In this study we measured information sharing using self-reports. However, self-reports of frequent and routine behaviors are often imprecise and unreliable (Scharkow, 2016). This represents a profound limitation of our study; whenever possible, future studies should aim to collect objective observations of specific types of behavior.

Finally, please note that the hypotheses presented in this study were not formally preregistered. At the time when the study was conceived in 2014, we were not yet aware of the importance of preregistration.

Future Research

We emphasize that when analyzing the privacy paradox we are likely dealing with small effects (Baruh et al., 2017). Hence, to detect these small effects reliably we need large samples. This is often not the case (Baruh et al., 2017). In conclusion, it is crucial to use statistical designs that allow for sufficient statistical power.

Next, evidence of within-person longitudinal effects is still missing. Although we found significant within-person correlations at T1, they were absent across the 6-month intervals. Together, this suggests that longitudinal effects might exist, but that they take place on a different time interval. Future research could hence probe different intervals. For theoretical reasons (e.g., due to availability heuristics), it is plausible to use short intervals; for statistical reasons (e.g., because of the high stability of privacy concerns), it would also make sense to test longer intervals (Dormann and Griffin, 2015).

In general, we emphasize that our findings should not be overgeneralized. They are conditional on the data we collected, the methods we applied, and the theoretical perspectives we adopted. We stress that analyzing the privacy paradox in other contexts using alternative approaches will likely lead to different results. Although we argue that in

556 most circumstances privacy concerns and behavior should correlate modestly, the exact

557 extent depends on a many boundary conditions. Future research should hence explicitly

558 analyze different contexts (Nissenbaum, 2010) and situations (Masur, 2018). Building on

559 Kokolakis (2017), we suggest to analyze the following boundary conditions:

560 • Context (e.g., professional, social, commercial, or health-related);

561 • Situation (e.g., new, habitualized, or unexpected);

562 • Mood (e.g., positive vs. negative);

563 • Extent of control (high vs. low);

564 • Type of information processing applied (implicit, heuristic, or peripheral vs. explicit,

565   analytic, or central);

566 • Existence of bias (e.g., overconfidence, optimism, comparative optimism, or

567   hyperbolic discounting);

568 • Type of information (e.g., sensitive vs. superficial, biographic, or person-related);

569 • Benefit immediacy and risk diffusion (high vs. low);

570 • Object of investigation (e.g., individual people, interactions between people,

571   developmental perspectives, critical incidents, societal structures, or historical

572   developments).

573   Specifically, we encourage analyzing privacy behaviors also from a situational

574 perspective, accounting for temporal needs, interpersonal perceptions, contextual cues, or

575 characteristics of communication channels (Masur, 2018). For example, whereas general

576 levels of information sharing are likely best explained using privacy *concerns*, situational

577 information sharing might be best explained using privacy *heuristics* (Sundar et al., 2013).

578   Next to these theory-related boundary conditions there are also methodological ones:

579 • Analysis design and perspective (e.g., theoretical, experimental, questionnaire-based,

580   interview-based, ethnographic, or computational);

581   • Quality of measurement (high vs. low; low quality less likely to detect statistical

582   significance);

583   • Sample size (small vs. large; small samples less likely to detect statistical significance);

584   • Statistical analysis (e.g., SEM vs. Regression; analyses without error control less

585   likely to find statistical significance);

586   • Operationalization (e.g., concerns vs. risk perceptions vs. behavioral attitudes; the

587   more specific, the stronger the relation).

588   **Conclusion**

589   Being able to show that online behaviors are not paradoxical can be socially relevant.

590   Consider the similar case of fear appeals and protective behavior, where there is also only a

591   small correlation (Witte and Allen, 2000). However, fear appeals are used in public

592   campaigns nonetheless, oftentimes to much success (Wakefield et al., 2010). Likewise,

593   proclaiming that the online sharing of personal information is not paradoxical and that

594   concerns about online privacy matter, could lead to more cautious and reflective behavior.

595   It is probably no coincidence that the General Data Protection Regulation, which

596   strengthens the privacy rights of consumers, was passed in Europe, where privacy concerns

597   are particularly pronounced (European Commission, 2015).

598   In sum, this study showed that when people were more concerned about their

599   privacy, they also shared a little less personal information about themselves online. If

600   respondents considered sharing personal information to be insensible, they disclosed

601   substantially less information. Together, these findings do not support the existence of a

602   privacy paradox, at least in this particular context and operationalization. No evidence of

603   long-term effects was found, however. Further research is needed to understand the

604   potential causal interplay of concerns, attitudes, and behavior.

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