1   A Longitudinal Analysis of the Privacy Paradox

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20   Abstract

21   The privacy paradox states that people's concerns about online privacy are unrelated to

22   their online sharing of personal information. Using a representative sample of the German

23   population, which includes NOT AVAILABLE respondents who were interviewed at three

24   waves separated by 6 months, we investigate the privacy paradox from a longitudinal

25   perspective. We differentiate between-person relations from within-person effects. Results

26   of a cross-lagged panel model with random intercepts revealed that people who were more

27   concerned about their online privacy than others also shared slightly less personal

28   information online and had substantially more negative attitudes toward information

29   sharing (between-person level). People who were more concerned than usual also shared

30   slightly less information than usual (within-person level). We found no long-term effects of

31   privacy concerns on information sharing or attitudes 6 months later. The results provide

32   further evidence against the privacy paradox, but more research is needed to better

33   understand the variables' potential causal relation.

34   *Keywords:* privacy paradox, privacy concerns, information sharing, longitudinal

35   analysis, structural equation modeling

36   Word count: 6581

³⁷ A Longitudinal Analysis of the Privacy Paradox

³⁸ **Introduction**

³⁹   The privacy paradox states that the information disclosure of Internet users is

⁴⁰ problematic: Although many people are concerned about their online privacy, they still

⁴¹ share plenty of personal information on the web (e.g., Acquisti & Grossklags, 2003). The

⁴² privacy paradox and its underlying theoretical conundrum is hence of considerable interest

⁴³ to society—it is discussed in newspapers (Frean, 2017), Wikipedia entries (Wikipedia,

⁴⁴ 2018), designated websites (New York Public Radio, 2018), books (Trepte & Reinecke,

⁴⁵ 2011), and top-tier academic journals (Acquisti, Brandimarte, & Loewenstein, 2015). If the

⁴⁶ privacy paradox really exists, it should inspire worry: It would suggest that online behavior

⁴⁷ is irrational and that people are revealing too much of their personal lives to unknown

⁴⁸ third parties, which can cause various problems (e.g., Sevignani, 2016). Understanding why

⁴⁹ people disclose information online and whether or not this is paradoxical therefore

⁵⁰ represents an important challenge.

⁵¹   However, current research on the privacy paradox has one major limitation: To the

⁵² best of our knowledge, most empirical studies conducted so far have investigated the

⁵³ privacy paradox from a between-person (i.e., interpersonal) perspective. By employing

⁵⁴ empirical tests of relations between people (e.g., cross-sectional questionnaires analyzed

⁵⁵ with multiple regression or Pearson correlations), studies have analyzed whether people

⁵⁶ who are more concerned than *others* also share less personal information than *others*.

⁵⁷ Although such a between-person perspective is interesting and represents a viable first

⁵⁸ step, it cannot make informed claims regarding causality. The privacy paradox, however,

⁵⁹ implies a causal perspective: Does a person, if *he or she* becomes more concerned about

⁶⁰ online privacy, then also share less personal information? This mismatch is problematic

⁶¹ because although between-person relations are, except for some special cases, a *necessary*

⁶² condition for causal within-person effects, they are by no means a *sufficient* one. For

⁶³ example, it could be that the between-person relation is determined other third variables.

64 Hence, as the next step in investigating the privacy paradox and to better understand the

65 causal relation between privacy concerns and information sharing, it is necessary to

66 conduct studies with within-person designs.

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

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

69 information? Second, on a within-person level, does information sharing decrease when

70 concerns increase? Third, what are the potential long-term effects, are changes in concerns

71 related to changes in information sharing 6 months later and/or vice versa? Fourth, what

72 is the role of privacy attitudes, do they mediate the relation between privacy concerns and

73 information sharing? To best answer and contextualize these questions, we first provide an

74 in-depth theoretical analysis of the privacy paradox, after which we present the empirical

75 results of a longitudinal panel study.

A Brief History of the Privacy Paradox

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

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

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

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

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

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

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

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

85 Norberg, Horne, and Horne (2007) were one of the first to empirically analyze the privacy

86 paradox explicitly. The study found a mismatch between concerns and behavior, which is

87 aligned with several other experimental studies conducted at the time (Beresford, Kübler,

88 & Preibusch, 2012; Hann, Hui, Lee, & Png, 2007; Huberman, Adar, & Fine, 2005).

89   While there are various understandings and operationalizations of the privacy

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 & Acquisti, 2005; Taddicken, 2014; Tufekci, 2008), which lends credence to the privacy paradox, a different set of studies showed significant relations (e.g., Dienlin & Trepte, 2015; Heirman, Walrave, & Ponnet, 2013; Walrave, Vanwesenbeeck, & Heirman, 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 mentioned explicitly. Instead, studies have referred to the so-called *privacy calculus*, which states that sharing personal information is affected by both the respective costs and the anticipated benefits (Culnan & 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 & Metzger, 2016; Krasnova, Spiekermann, Koroleva, & Hildebrand, 2010).

Baruh, Secinti, and Cemalcilar (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, Li, He, Wang, and Jiao (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 & Jong, 2017; Gerber, Gerber, & Volkamer, 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

117 solve the problem of the privacy paradox are still scarce and we feel the subject deserves

118 far more research attention" (p. 1052).

Defining Privacy Concerns and Information Sharing

120   Privacy is defined as the "[. . .] voluntary and temporary withdrawal of a person from

121 the general society through physical or psychological means [. . .]" (Westin, 1967, p. 7).

122 Hence, privacy captures aspects of both volitional *control* and social *separateness*. Several

123 dimensions of privacy have been proposed. For example, it is possible to distinguish a

124 vertical and a horizontal level. Whereas the vertical level captures privacy from authorities,

125 institutions, or companies, horizontal privacy addresses privacy from peers, colleagues, or

126 other people (Masur, 2018). When it comes to concerns in general, interestingly they do

127 not seem to be established as a stand-alone theoretical concept in psychology (Colman,

128 2015). Lexically, concerns are defined as a "marked interest or regard usually arising

129 through a personal tie or relationship" that also reflect an "uneasy state of blended

130 interest, uncertainty, and apprehension" (Merriam-Webster, 2018). Concerns therefore

131 represent both a latent *motivation* (or increased attention), a negatively valenced *emotion*

132 (or affective condition), and are mostly implicit. As a theoretical construct, privacy

133 concerns can hence be categorized as an affective motivational disposition. As such, there

134 are many similarities with other concepts, including emotions (e.g., fear, anxiety), moods

135 (e.g., dismay, fatigue), attitudes (risk perception, approval), values (e.g., autonomy,

136 freedom), personality traits (e.g., introversion, risk avoidance), and even physiological

137 activation (e.g., attention, arousal). Taken together, concerns about online privacy

138 represent how much an individual is motivated to focus on his or her control over a

139 voluntary withdrawal from other people or societal institutions on the Internet,

140 accompanied by an uneasy feeling that his or her privacy might be threatened.

141   The online sharing of personal information, on the other hand, captures how much

142 person-related information people share when they use the Internet, including information

about their age, sex, name, address, health, and finances. 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, Bavelas, Jackson, & O'Hanlon, 2011). Self-disclosure is narrow, because it focuses on deliberate revelations about the true self to others (e.g., Jourard, 1964). Information sharing is even more specific, because it addresses only person-related information but ignores other types of self-disclosure such as personal fears, values, or plans.

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 profoundly (Fishbein & 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. People more concerned about the environment show more environment-related behaviors (Bamberg, 2003). People more concerned about their appearance consume fewer calories (Hayes & Ross, 1987). People more concerned about their bodies engage in more physical exercise (Reel et al., 2007). Taken together, it is reasonable to expect that also concerns about online privacy should reflect in the online sharing of personal information.

At the same time, there are some factors that are likely to diminish the relation. Most prominently, there is the so-called *attitude behavior gap* (Fishbein & Ajzen, 2010), which states that people sometimes act against their own attitudes. Not everyone concerned about his or her 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. Specifically, two of the most influential factors that affect online information sharing are (a) strong subjective norms (Heirman et al., 2013) and (b) expected benefits(Krasnova et al., 2010). In other words, users often prioritize social support, special offers, or improved services. Trepte, Dienlin, and Reinecke (2014) listed several factors that can additionally attenuate the relation: lack of strength of concerns, absence of negative personal experiences, or situational constraints due to social desirability. In conclusion, also in the context of the privacy paradox we should not expect to find a perfect relation between attitudes and behaviors. Expecting a small to moderate relation is more reasonable.

Finally, there are also some methodological explanations why some studies did not detect statistically significant relations. Researchers are always confronted with the so-called *Duhem-Quine problem*, which holds that it is impossible to test theories in isolation, because empirical tests always rely on auxiliary assumptions (Dienes, 2008). In other words, if a psychological experiment fails, we do not know whether the theory is wrong or the questionnaire subpar. This tenet is particularly relevant for the privacy paradox: Detecting statistical significance for small effects—and in this case, we should expect to find small effects—is more challenging because it means that large samples are necessary to guarantee sufficient statistical power.[1] Precisely, in order to be capable of detecting a correlation between privacy concerns and information sharing in 95% of all cases, which 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, in line with prior research and the within-person rationales presented above, we expect to find a small significant relation between privacy concerns and

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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).

¹⁹⁴ information sharing, both on the between-person level and the within-person level.

¹⁹⁵   Hypothesis 1: People who are more concerned about their online privacy than others

¹⁹⁶ will also be less likely to share personal information online than others.

¹⁹⁷   Hypothesis 2: People who are more concerned about their online privacy than they

¹⁹⁸ usually are will also share less personal information online than they usually do.

Long-Term Perspective

²⁰⁰   Although short-term effects are likely, it is still unclear whether long-term effects

²⁰¹ exist as well. First, when analyzing potential long-term effects, it is important to choose an

²⁰² interval that is both plausible and relevant. (It makes a large difference whether the effects

²⁰³ of alcohol consumption on driving performance are tested after 1 minute, 1 hour, or 1 day.)

²⁰⁴ One factor that determines an interval's optimal length is the stability of the variables

²⁰⁵ (Dormann & Griffin, 2015). Privacy concerns and privacy attitudes are predominantly

²⁰⁶ trait-like constructs with high stabilities, which is why they necessitate longer intervals.

²⁰⁷ Other studies with comparable research questions have used an interval of 6 months (e.g.,

²⁰⁸ Valkenburg & Peter, 2009), which we consider to be plausible also in this case.

²⁰⁹   In general, we believe that it should be possible to find long-term effects. It has been

²¹⁰ argued that privacy concerns affect privacy behavior in the long run (e.g., Heirman et al.,

²¹¹ 2013). The underlying theoretical mechanism could be that the emotional part of privacy

²¹² concerns causes (a) motivated information selection and (b) motivated information

²¹³ processing, which is likely to change actual behavior (Nabi, 1999). Specifically, when

²¹⁴ privacy concerns increase (e.g., because of experienced or witnessed privacy infringements),

²¹⁵ people might begin reading more media articles on privacy issues and might also consume

²¹⁶ these articles more carefully, which could prompt information sharing practices that are

²¹⁷ more cautious. Also empirically, a study with 290 participants found small negative

²¹⁸ longitudinal (between-person) relations between privacy concerns and self-disclosure

²¹⁹ (Koohikamali, French, & Kim, 2019).

²²⁰ At the same time, the adverse effect of information sharing on privacy concerns seems

²²¹ plausible as well, with two potential outcomes. On the one hand, the long-term relation

²²² could be negative: If people start to share more information online, they might become

²²³ increasingly aware that their privacy is at risk, thereby stirring concern. On the other

²²⁴ hand, the long-term relation might also be positive: When people share more personal

²²⁵ information online they might become accustomed to doing so, which potentially reduces

²²⁶ concern (for example, due to the mere exposure effect; Zajonc, 1968). Finally, there could

²²⁷ also be no long-term relation at all: People might have already become used to sharing

²²⁸ information online, which stifles further cognitive or emotional processing. This rationale is

²²⁹ central to so-called *privacy cynicism* (e.g., Hoffmann, Lutz, & Ranzini, 2016).

²³⁰ Research Question 1.1: Do changes in concerns about online privacy affect the online

²³¹ sharing of personal information 6 months later?

²³² Research Question 1.2: Do changes in the online sharing of personal information

²³³ affect concerns about online privacy 6 months later?

The Role of Attitudes

²³⁵ It has been argued that privacy attitudes could bridge the gap between concerns and

²³⁶ information sharing (e.g., Dienlin & Trepte, 2015). In contrast to privacy concerns, privacy

²³⁷ attitudes capture a more explicit, fluctuating cognitive appraisal. Although both variables

²³⁸ are related to information disclosure, attitudes are likely the better predictor. This

²³⁹ reasoning follows the rational choice paradigm (Simon, 1955), which maintains that

²⁴⁰ behavior is always at least partially influenced by convictions, attitudes, and cost-benefit

²⁴¹ analyses. Also empirically, a study of 1,042 youths from Belgium found that the relation

²⁴² between privacy attitudes and disclosure of personal information was strong ($r = .56$),

²⁴³ whereas the relation between privacy concerns and disclosure was only moderate ($r = -.29$;

²⁴⁴ Heirman et al., 2013).

²⁴⁵ 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.

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

toward the online sharing of personal information 6 months later?

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

information affect concerns about online privacy 6 months later?

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

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

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

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

269   **Method**

270 **Statistics**

271   We follow the recommendation by Daniel Lakens et al. (2018) and first justify the

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

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

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

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

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

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

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

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

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

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

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

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

284 support for our theoretical hypotheses; significantly smaller effects were not considered able

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

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

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

288 of $\beta = 0.10$, we calculated a minimum sample size of 1,293 respondents. Given the final

289 sample size of 1,403 respondents (see below), alpha and beta errors were balanced for our

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

291 power of 97% (95.80%) to detect small effects.

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

293 (RI-CLPM) (Hamaker, Kuiper, & Grasman, 2015). For a visualization, see Figure 1. Note

294 that in contrast to regular cross-lagged panel models (CLPMs), RI-CLPMs can separate

295 between-person variance from within-person variance. We used factor scores as observed
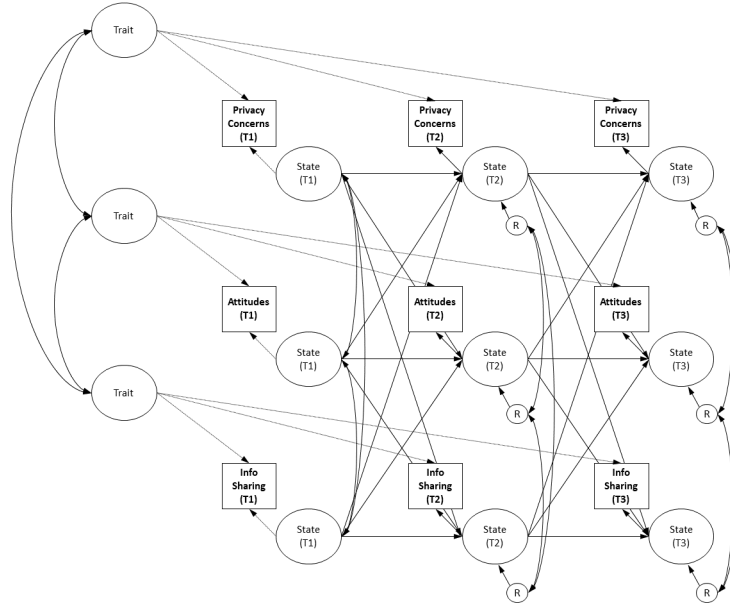
Figure 1. Visual representation of the estimated random-intercept cross-lagged panel model (RI-CLPM).

variables to represent the variables' latent structure more closely. We tested H1, H3.1, and H3.2 by correlating the random intercepts, which represent the respondents' individual mean scores across all three waves. We tested H2, H4.1, and H4.2 by correlating the respondents' within-person variance at T1, which captures their specific deviation at T1 from their overall score. We tested all research questions by regressing variables on all other measures obtained 6 months earlier. Given that we had three points of measurement, this resulted in two estimates for each research question. As we did not assume longitudinal effects to 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 $= .01$.

310   For the analyses, coding, and typesetting, we used R (Version 3.6.1; R Core Team,

311 2018) and the R-packages *GGally* (Version 1.4.0; Schloerke et al., 2018), *ggplot2* (Version

312 3.2.1; Wickham, 2016), *lavaan* (Version 0.6.5; Rosseel, 2012), *MissMech* (Version 1.0.2;

313 Jamshidian, Jalal, & Jansen, 2014), *MVN* (Version 5.8; Korkmaz, Goksuluk, & Zararsiz,

314 2014), *psych* (Version 1.9.12.31; Revelle, 2018), *pwr* (Version 1.2.2; Champely, 2018),

315 *semTools* (Version 0.5.2; Jorgensen et al., 2018), and *sjstats* (Version 0.17.9; Lüdecke,

316 2019). The code, additional analyses, and a reproducible version of this manuscript can be

317 found on the manuscript's companion website at

318 https://tdienlin.github.io/privacy-paradox-longitudinal.

Procedure and Respondents

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

321 privacy and self-disclosure, including severaldother variables. Other publications linked to

322 the project can be accessed at https://osf.io/y35as/. The data come from a longitudinal

323 paper-and-pencil questionnaire study, in which a representative sample of the German

324 population (16 years and older) was surveyed on overall five occasions. The data can be

325 downloaded from http://dx.doi.org/10.7802/1937.

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

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

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

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

330 14,714 potential respondents was drawn from a representative omnibus survey in Germany

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

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

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

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

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

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

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

$n = 1,403$ respondents.

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

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

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

Therefore, Full Information Maximum Likelihood (FIML) estimation was conducted using

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

About 39% reported that they had graduated from college.

Measures

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

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

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

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

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

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

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

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

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

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

found in the OSM.

Concerns about online privacy.   Privacy concerns were measured as a

second-order factor. Three items captured the vertical dimension (e.g., "How concerned are

you that institutions or intelligence services collect and analyze data that you disclosed on

the Internet?"), and three items captured the horizontal dimension (e.g., "How concerned

are you that people that you do not know might obtain information about you because of

362 you online activities?"). Respondents rated all items on a 5-point scale ranging from 1 (*not*

363 *at all concerned*) to 5 (*very concerned*). The means were $M_{t1} = 3.67$, $M_{t2} = 3.62$, $M_{t3} =$

364 3.59, and the standard deviations $SD_{t1} = 0.88$, $SD_{t2} = 0.89$, and $SD_{t3} = 0.90$. The

365 two-dimensional model fit the data well, $\chi^2(118) = 661.17$, $p < .001$, cfi = .97, rmsea = .06,

366 90% CI [.05, .06], srmr = .04. The reliability was high ($\omega_{t1} = .95$, $\omega_{t2} = .96$, $\omega_{t3} = .97$).

367 Overall, 73.85% of the measure's variance was explained by differences between persons.

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

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

370 information on the Internet. The exact question was: "How often do you disclose the

371 following pieces of information online (i.e., on the Internet)?" Each item was answered on a

372 5-point scale ranging from 1 (*never*) to 5 (*daily*). Factor analyses suggested a second-order

373 factor structure with five first-order factors of two items each. The first first-order factor

374 subsumed financial and medical information, the second first and last name, the third place

375 of residence and street (including house number), the fourth email address and phone

376 number, and the fifth information about education and current job. The means were M_{t1}

377 $= 2.12$, $M_{t2} = 2.13$, $M_{t3} = 2.10$, and the standard deviations $SD_{t1} = 0.66$, $SD_{t2} = 0.64$,

378 and $SD_{t3} = 0.61$. The model fit the data adequately, $\chi^2(375) = 2527.69$, $p < .001$, cfi =

379 .95, rmsea = .06, 90% CI [.06, .07], srmr = .06. The reliability was high ($\omega_{t1} = .91$, $\omega_{t2} =$

380 .92, $\omega_{t3} = .91$). Overall, 64.29% of the measure's variance was explained by differences

381 between persons.

382 **Attitudes toward the online sharing of personal information.**   Respondents'

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

384 measured the general appraisal of disclosing the same 10 pieces of information. Adhering to

385 the principle of compatibility (Fishbein & Ajzen, 2010), the items were parallel to those of

386 the actual disclosure scale. Specifically, we asked: "Do you think that it is sensible to

387 disclose the following pieces of information online (i.e., on the Internet)?" The scale ranged

388 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.

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, Hypothesis 1 was supported.

Hypothesis 2 proposed that if people perceived more concerns about their online privacy than they usually do, they would also share less personal information online than they usually do. Results revealed a small significant correlation ($\beta = -.10$, $b = -0.02$, 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
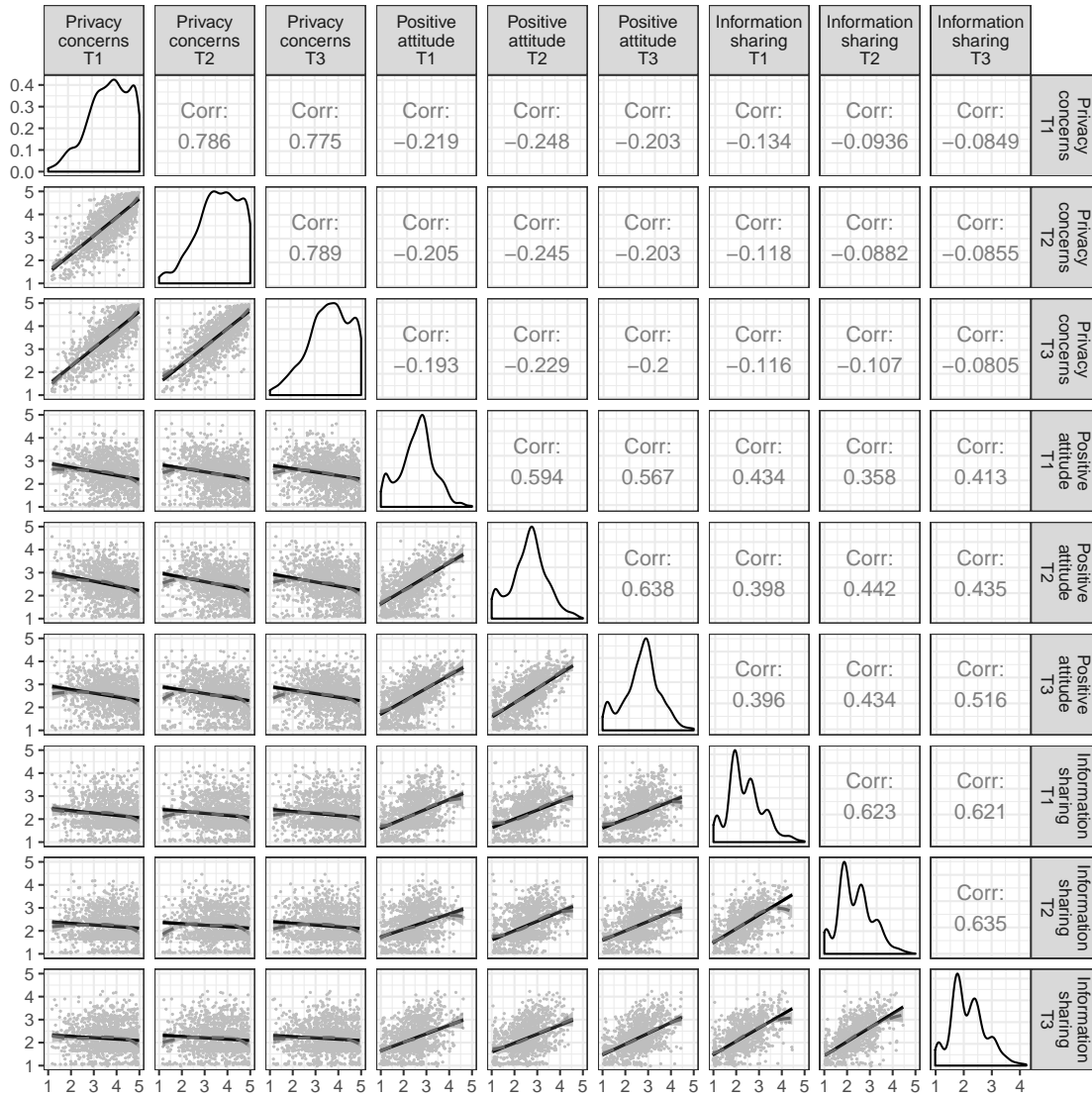
Figure 2. Results of the bivariate relations. Above the diagonal: zero-order correlation matrix; diagonal: density plots for each variable; below the diagonal: bivariate scatter plots for zero-order correlations. Solid regression lines represent linear regressions, dashed regression lines represent quadratic regressions. Calculated with the variables' latent factor scores.

lagged effect across 6 months was found ($\beta = .01$, $b = 0.01$, 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 would also hold more negative attitudes toward the online sharing of personal information than usual. The results did not reveal a significant effect (β = -.06, b = -0.01, 95% CI [-0.03, < 0.01], z = -1.38, p = .084). Hypothesis 4.2 proposed that people who held more positive attitudes toward the online sharing of personal information than usual would also share more personal information online than usual. Results showed a moderate within-person correlation between the two variables (β = .15, b = 0.03, 95% CI [0.02, 0.05], z = 4.01, p < .001), which indicates that when respondents had more positive attitudes at T1 than usual, they also shared more personal information than usual. In conclusion, the results supported Hypothesis 4.2.

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

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

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

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

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

450 [-0.06, 0.06], z = 0.06, p = .951).

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

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

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

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

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

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

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

458   Table 1 presents an overview of all results.

Discussion

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

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

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

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

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

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

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

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

468 variables' causal relationship.

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

470 concerned about their privacy than others also shared personal information slightly less

Table 1

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

Effect	b	95% CI ll	ul	beta	p
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.

frequently. In addition, people who were more concerned about their privacy than others also held substantially more negative attitudes toward disclosing personal information online. Notably, we found a very strong between-person correlation between attitudes toward information sharing and actual information sharing. This finding shows that typical online disclosure can be predicted precisely by a person's attitude. Taken together, the cross-sectional results are in line with the extant literature: The between-person correlation of privacy concerns and information sharing found in this study (i.e., $\beta = -.08$) fall within the 95% confidence interval of the effect reported by Baruh et al. (2017) (i.e., $r = -.13$, 95% CI [-.07, -.18]). Note that the between-person correlations reported here represent averaged measurements across three waves, which should make the findings more robust than typical one-shot measures.

In conclusion, this study suggests that the privacy paradox does not exist on a between-person level. The differences between people with regard to their online information sharing behavior can be explained by differences in privacy concerns to a small extent, and by differences in privacy attitudes to a large extent. The more specific we become, the better we can explain online behavior: Whereas privacy concerns are related only weakly to online information sharing (e.g., Baruh et al., 2017), more specific risks perceptions are related to behavior more closely (e.g., Bol et al., 2018; Yu et al., 2020), whereas behavioral attitudes are the best predictors (Dienlin & Trepte, 2015).

The within-person results showed that when a person's privacy concerns increased, the same person also shared slightly less information online than usual. Moreover, people who developed more positive attitudes toward the online sharing of personal information than usual, also shared substantially more personal information online. Together, changes in concerns and attitudes are both related to changes in behavior, which speaks against the privacy paradox also on the within-person level.

We did not find any long-term effects, however. Changes in both privacy concerns and attitudes toward the online sharing of personal information were not related to any

meaningful changes in the online sharing of personal information 6 months later, and vice versa. As an explanation, it might be the case that changes in privacy concern affect information sharing more immediately. To test this assumption, we would need study designs with shorter intervals (Keijsers, 2016). Moreover, given that the directions of most longitudinal relations were in line with the between-person and within-person relations, longitudinal effects might indeed take place, but only that they are very small. Of course, it could also be that longterm longitudinal effects do not exist.

Limitations

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, p. 204), which states that all psychosocial measures are related to one another to some extent. On the other hand, other factors such as expected benefits might play a more important role (Dienlin & 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 surely 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 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

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), however, it also makes sense to test longer intervals (Dormann & Griffin, 2015).

Although we argue that in most circumstances privacy concerns and behavior should correlate modestly, the exact extent depends on a many boundary conditions. Future research should hence explicitly analyze different contexts and situations. Building on Kokolakis (2017), we suggest the following boundary conditions:

- Context (e.g., professional, social, commercial, or health-related);
- Situation (e.g., new, habitualized, or unexpected);
- Mood (e.g., positive vs. negative);
- Extent of control (high vs. low);
- Type of information processing applied (implicit, heuristic, or peripheral vs. explicit, analytic, or central);
- Existence of bias (e.g., overconfidence, optimism, comparative optimism, or hyperbolic discounting);
- Type of information (e.g., sensitive vs. superficial, biographic, or person-related);
- Benefit immediacy and risk diffusion (high vs. low).

Specifically, we encourage analyzing privacy behaviors also from a situational perspective, accounting for temporal needs, interpersonal perceptions, contextual cues, or characteristics of communication channels (Masur, 2018). For example, whereas general levels of information sharing are likely best explained by using privacy *concerns*, situational information sharing might be best explained using privacy *heuristics* (Sundar, Kang, Wu, Gu, & Zhang, 2013).

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

550   • Analysis design (e.g., theoretical, experimental, questionnaire-based, interview-based,

551   or anecdotal);

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

553   significance);

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

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

556   likely to find statistical significance);

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

558   more specific, the stronger the relation).

559   When analyzing the privacy paradox we are likely dealing with small effects (Baruh

560 et al., 2017). Hence, to detect these small effects reliably we need large samples. This is

561 often not the case (Baruh et al., 2017). In conclusion, we emphasize to use statistical

562 designs that allow for sufficient statistical power.

Conclusion

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

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

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

567 campaigns nonetheless, oftentimes to much success (Wakefield, Loken, & Hornik, 2010).

568 Likewise, proclaiming that the online sharing of personal information is not paradoxical

569 and that concerns about online privacy matter, could lead to more cautious and reflective

570 behavior. It is probably no coincidence that the General Data Protection Regulation,

571 which strengthens the privacy rights of consumers, was passed in Europe, where privacy

572 concerns are particularly pronounced (European Commission, 2015).

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

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

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

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

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

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

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

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