A Longitudinal Analysis of the Privacy Paradox

Tobias Dienlin[1], Philipp K. Masur[2], & Sabine Trepte[1]

[1] University of Hohenheim

Johannes Gutenberg University Mainz

Author Note

Abstract

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

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

Word count: 6863

₃₅ A Longitudinal Analysis of the Privacy Paradox

₃₆ The privacy paradox states that information disclosure practices of Internet users are

₃₇ problematic: Although many people are concerned about their online privacy, they still tend

₃₈ to disclose plenty of personal information on the web (e.g., Acquisti & Grossklags, 2003).

₃₉ This is problematic, because sharing information online allows to accurately predict a

₄₀ person's future behavior (Bagrow, Liu, & Mitchell, 2019). The privacy paradox and its

₄₁ underlying theoretical conundrum is hence of considerable interest to society—it is discussed

₄₂ in newspapers (Frean, 2017), Wikipedia (Wikipedia, 2018), designated websites (New York

₄₃ Public Radio, 2018), books (Trepte & Reinecke, 2011), and top-tier academic journals

₄₄ (Acquisti, Brandimarte, & Loewenstein, 2015). If the privacy paradox really exists, it should

₄₅ inspire worry: It would suggest that online behavior is irrational and that people are

₄₆ revealing too much of their personal lives to unknown third parties, fostering potentially

₄₇ unintended consequences such as commodification, exploitation or inappropriate

₄₈ recontextualization (boyd, 2008; Sevignani, 2016). In conclusion, understanding why people

₄₉ disclose information online and whether this is paradoxical or not represents an important

₅₀ challenge for communication scholars.

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

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

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

₅₄ tests of between-person variance (e.g., cross-sectional questionnaires analyzed with multiple

₅₅ regression or Pearson correlations), studies have analyzed whether people who are more

₅₆ concerned than *others* also share less personal information than *others*. Granted, such a

₅₇ between-person perspective is interesting and represents a viable first step in analyzing the

₅₈ relation between these variables. At the same time, it is important to emphasize that the

₅₉ privacy paradox actually implies that the research question that should be asked is a

₆₀ within-person (i.e., intrapersonal) relation: Does a person, if *he or she* becomes more

₆₁ concerned about online privacy, then also share less personal information? This mismatch is

[62] problematic because although between-person variance is, except some specific cases, a

[63] *necessary* condition for within-person effects, it is by no means a *sufficient* condition. For

[64] example, it could be that the between-person relation is determined by another stable third

[65] variable. Hence, as the next step in investigating the privacy paradox and to better

[66] understand the intrapersonal relation between privacy concerns and information sharing, we

[67] now need studies with within-person designs.

[68] As a result, with this study we aim to answer four major questions. First, on a

[69] between-person level, how are concerns about online privacy related to the online sharing of

[70] personal information? Second, on a within-person level, does information sharing decrease

[71] when concerns increase? Third, what are the potential long-term effects, are changes in

[72] concerns related to changes in information sharing 6 months later and/or vice versa? Fourth,

[73] what is the role of privacy attitudes, do they mediate the relation between privacy concerns

[74] and information sharing? To best answer and contextualize these questions, we first provide

[75] an in-depth theoretical analysis of the privacy paradox, after which we present the empirical

[76] results of a longitudinal panel study.

A Brief History of the Privacy Paradox

[78] Acquisti and Grossklags (2003) were among the first to argue that the online disclosure

[79] of personal information is paradoxical. "Experiments reveal that very few individuals

[80] actually take any action to protect their personal information, even when doing so involves

[81] limited costs" (p.1). Three years later, Barnes (2006) discussed the behavior of young people

[82] using SNSs and coined the expression the "privacy paradox." Barnes listed six notions that

[83] she considered to be particularly paradoxical: (a) illusion of privacy, (b) high quantity of

[84] information sharing, (c) attitude behavior discrepancy, (d) lack of privacy concerns, (e) lack

[85] of privacy literacy, and (f) fabrication of false information.

[86] Subsequent research analyzed the privacy paradox more explicitly, focusing on Barnes's

[87] third tenet, the attitude-behavior discrepancy. On the one hand, 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), lending credence to the privacy paradox. On the other hand, a different set of studies showed relations that were statistically significant (Heirman, Walrave, & Ponnet, 2013; Walrave, Vanwesenbeeck, & Heirman, 2012; e.g., Dienlin & Trepte, 2015), thereby refuting the privacy paradox.

It is interesting that in a parallel line of research, other studies have also analyzed the relation between privacy concerns and subsequent information sharing; however, the term privacy paradox has often not been mentioned explicitly. Instead, studies have referred to the so-called *privacy calculus.* The privacy calculus states that sharing personal information is affected by both the respective costs and the anticipated benefits (Culnan & Armstrong, 1999) and by now, several studies have found empirical support 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 ($r = -.13$). For other systematic literature reviews, see Barth and Jong (2017), Gerber, Gerber, and Volkamer (2018), and Kokolakis (2017). In conclusion, the current literature suggests that a significant relation between concerns about online privacy and the online sharing of personal information exists and that it is small—which speaks against the privacy paradox.

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, p. 7). Hence, privacy captures aspects of both volitional *control* and social *separateness.* Several

dimensions of privacy have been proposed: For example, it is possible to distinguish a vertical and a horizontal level; whereas the vertical level captures privacy from authorities, institutions, or companies, horizontal privacy addresses privacy from peers, colleagues, or other people (Masur, 2018). When it comes to concerns, it is interesting that they do not seem to be established as a stand-alone theoretical concept in psychology; for example, the Oxford Dictionary of Psychology does not feature a designated entry (Colman, 2015). In general, however, concern is defined as a "marked interest or regard usually arising through a personal tie or relationship" that also reflects an "uneasy state of blended interest, uncertainty, and apprehension" (Merriam-Webster, 2018). A concern therefore partially represents a latent *motivation* (or increased attention) to invest oneself in a specific entity and a negatively valenced *emotion* (or affective cognition). As such, a concern is not predominantly the result of a deliberate explicit cognition; instead, it primarily reflects an automatic implicit perception. 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. As a theoretical construct, privacy concerns can hence be categorized as an affective motivational disposition. As such, they have similarities with many other concepts such as emotions (e.g., fear, anxiety), moods (e.g., dismay, fatigue), attitudes (approval, dissent), values (e.g., autonomy, freedom), personality traits (e.g., introversion, risk avoidance), and even physiological activation (e.g., attention, arousal).

The online sharing of personal information, on the other hand, captures how much person-related information people share when they use the Internet, including, for example, information about their age, sex, name, address, health, or finances. Information sharing can be differentiated from communication and self-disclosure: Whereas communication is broad because it includes 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)

The Relation Between Privacy Concerns and Information Sharing

It is somewhat surprising that the literature seems to lack explicit theoretical treatises on why and how human behavior should be specifically affected by concerns. More fortunately, however, there are several theoretical insights regarding how the affective motivational concepts presented above can pertain to behavior. The results are unanimous: They can all affect behavior profoundly. For example, let us consider the concept that is perhaps closest to concerns, emotions. By causing fight or flight reactions, emotions are potentially the most primordial trigger of behavior as they are considered an adaptive mechanism that fosters the evolution of a species (Dolan, 2002). With their direct link to the amygdala, emotions can already trigger reactions subcortically (i.e., without activation of the more recently evolved cortical structures; Dolan, 2002). It hence seems plausible to suggest that privacy concerns, with their emotional dependency, also share this function at least partially. Moreover, changes in concerns might be correlated with changes in behavior because people usually aim to reduce discrepancies between cognitions and behavior (Festinger, 1957). There are also several empirical accounts of how concerns affect behavior: People who are more concerned about the environment show more environment-related behaviors (Bamberg, 2003), people who are more concerned about their appearance consume fewer calories (Hayes & Ross, 1987), and people who are more concerned about their bodies engage in more physical exercise (Reel et al., 2007). Hence, it seems reasonable to also expect that if a person's concerns about online privacy change, this change should be reflected in a change in the extent to which this person will share personal information online.

At the same time, there are several variables that are likely to diminish the relation. Most prominently, there is the so-called "attitude behavior gap", which pertains to the idea that people often act against their own attitudes (e.g., Fishbein & Ajzen, 2010). For example, despite endorsing the importance of physical health, a large part of the population does not exercise regularly. Transferred to the privacy paradox, it should not be surprising to encounter this general discrepancy also in the specific context of privacy concerns and

168 information sharing. The explanation is simple: Other factors such as subjective norms and

169 perceived behavioral control can also determine behavior (Ajzen, 1985), and this

170 automatically limits the predictive capacity of attitudes or concerns. Specifically, two of the

171 most influential factors that affect online information sharing are (a) the strong subjective

172 norms to participate online (Heirman et al., 2013) and (b) the manifold benefits that accrue

173 from participation (Krasnova et al., 2010). In other words, instead of considering privacy

174 concerns it is often more important to attain social support, special offers, or tailored

175 services. Trepte, Dienlin, and Reinecke (2014) listed several factors that can additionally

176 attenuate the relation: if the concerns miss any actual strength, a lack of negative personal

177 experiences, or distortions due to situational constraints such as social desirability.

178   Finally, there are also some methodological reasons that can explain why some studies

179 did not find statistically significant relations even though they probably exist empirically. In

180 general, researchers are always confronted with the so-called Duhem-Quine problem, which

181 holds that it is impossible to test theories in isolation, because empirical tests always rely on

182 auxiliary assumptions (e.g., Dienes, 2008). In other words, if a psychological experiment fails,

183 we do not know whether the theory is wrong or the questionnaire subpar. This tenet is

184 particularly relevant for the privacy paradox: Detecting statistical significance for small

185 effects—and in this case, we should expect to find effects that are small—is more challenging

186 because it means that large samples are necessary to guarantee sufficient statistical power.[1]

187 Precisely, in order to be capable of detecting a correlation between privacy concerns and

188 information sharing in 95% of all cases, which Baruh et al. (2017) estimated to be $r = -.13$,

189 we need a sample of $N = 762$ people. The reality, however, looks different: In their

190 meta-analysis, Baruh et al. reported a median sample size of $N = 300$.

191   To conclude, in line with prior research (Baruh et al., 2017) and the within-person

192 rationales that we have presented above, we first expected to find a significant relation

[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).

between privacy concerns and information sharing both on the between-person level and the within-person level. Second, given the strong premise that concerns should be reflected in contiguous behaviors, alongside the existence of several diminishing factors, we expected to find a small relation between concerns about online privacy and the online sharing of personal information also on the within-person level.

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 we hypothesized that changes in people's concerns about online privacy will be directly reflected by their behavior, we were not sure about whether there would also be long-term effects. First, when analyzing potential long-term effects, it is important to choose an interval that is both plausible and relevant. For example, it makes a difference whether the effects of alcohol consumption on driving performance are tested 1 min, 1 h, or 1 day after consumption. One factor that determines an interval's optimal length is the variable's stability (Dormann & Griffin, 2015). Privacy concerns and privacy attitudes are predominantly trait-like constructs with high stabilities, therefore necessitating longer intervals. Other studies with comparable research questions have used an interval of 6 months (e.g., Valkenburg & Peter, 2009), which we consider to be plausible also in this case.

In general, we believe that it should be possible to find long-term effects. It has been argued that privacy concerns *affect* privacy behavior (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 increase (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, French, & Kim, 2019).

At the same time, the adverse effect of information sharing on privacy concerns seems also plausible, with two potential outcomes. On the one hand, the long-term relation could be negative: If people start to share more information online, they might become increasingly aware that their privacy is at risk, which might stir concern. On the other hand, the long-term relation might also be positive, because when people share more personal information online, they might become accustomed to doing so, which might reduce concern (for example, due to the mere exposure effect; Zajonc, 1968). Finally, there could also be no long-term relation after all. For example, people might have already become used to sharing information online and this might stifle any further cognitive or emotional processing, a rationale central to the observation of so-called *privacy cynicism* (e.g., Hoffmann, Lutz, & Ranzini, 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 & Trepte, 2015). In contrast to privacy concerns, privacy attitudes capture a more explicit, fluctuating cognitive appraisal. Although both variables are related to information disclosure, attitudes are likely to be the better predictor. This reasoning follows the rational choice paradigm (Simon, 1955), which maintains that behavior is always, at least in part, influenced by convictions, attitudes, and cost-benefit analyses.

Likewise, evolutionary psychology also suggests that although emotions guide behavior in the long run, it is more adaptive if behavior instead reflects a cognitive appraisal; a tenet arguably reflected best by the phylogenetic development of the neocortex or the general dominion of the human race. These rationales have also found some empirical support. For example, 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 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, the same situation exists here as mentioned above: Given that no prior research exists on long-term relations, several scenarios seem plausible. For example, attitudes could either have long-term relations or not, and information sharing could either foster or diminish privacy attitudes.

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?

Method

Statistics

We follow the recommendation by Lakens et al. (2017) 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 would unjustly reassure and placate people when they should instead 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 to use error rates that are balanced. Next, we set a maximum error rate of 5% for both alpha and beta. As the smallest effect size of interest (SESOI; Lakens, 2014), 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 $\beta = 0.10$, we calculated that we needed a minimum sample size of 1,293 respondents. Given the final sample size of 1,403 respondents (see below), alpha and beta errors were balanced for our hypotheses (research questions) when we used a critical alpha of 3% (4.20%), resulting in a power of 97% (95.80%) to detect small effects.

298   The data were analyzed by means of a random-intercept cross-lagged panel model

299 (RI-CLPM) (Hamaker, Kuiper, & Grasman, 2015), a method that already has been used for

300 similar research questions (Dietvorst, Hiemstra, Hillegers, & Keijsers, 2018). Note that in

301 contrast to regular cross-lagged panel models (CLPMs), RI-CLPMs allow to separate

302 between-person variance from within-person variance. We used factor scores as observed

303 variables to represent the variables' latent structure more closely. We tested H1, H3.1, and

304 H3.2 by correlating the random intercepts, which represent the respondents' individual mean

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

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

307 score. We tested all research questions by regressing variables on all other measures obtained

308 6 months earlier. Given that we had three points of measurement, this resulted in two

309 estimates for each Research Question. As we did not expect longitudinal effects to differ

310 across time, they were constrained to be equal across all waves, thereby producing one single

311 general measure of each effect instead of two time-specific ones. Fit was assessed according

312 to the common criteria as described by Kline (2016). The final model fit the data well,

313 $\chi^2(15) = 25.18$, $p = .048$, cfi = 1.00, rmsea = .02, 90% CI [< .01, .04], srmr = .01.

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

315 2018) and the R-packages *GGally* (Version 1.4.0; Schloerke et al., 2018), *ggplot2* (Version

316 3.2.1; Wickham, 2016), *lavaan* (Version 0.6.5; Rosseel, 2012), *lme4* (Version 1.1.21; Bates,

317 Mächler, Bolker, & Walker, 2015), *magrittr* (Version 1.5; Bache & Wickham, 2014),

318 *MissMech* (Version 1.0.2; Jamshidian, Jalal, & Jansen, 2014), *papaja* (Version 0.1.0.9842;

319 Aust & Barth, 2018), *psych* (Version 1.8.12; Revelle, 2018), *pwr* (Version 1.2.2; Champely,

320 2018), *RVAideMemoire* (Hervé, 2019), *semTools* (Version 0.5.2; Jorgensen et al., 2018),

321 *sjstats* (Version 0.17.5; Lüdecke, 2019), *td* (Version 0.0.1; Dienlin, 2018), and *tidyverse*

322 (Version 1.2.1; Wickham, 2017). The code, additional analyses, and a reproducible version of

323 the manuscript can be accessed in the Online Supplementary Material (OSM) at

324 https://osf.io/4wabh.

Procedure and Respondents

This study is part of a large-scale project which investigates the development of privacy and self-disclosure, including several other variables. Other publications linked to the project can be accessed at https://osf.io/y35as/. The data come from a longitudinal, paper-and-pencil questionnaire study, in which a representative sample of the German population (16 years and older) was surveyed on overall five occasions. The data can be downloaded from http://dx.doi.org/10.7802/1937.

The first three waves were collected from May 2014 to May 2015, with intervals of 6 months each. The last two waves, collected on May 2016 and May 2017, had an interval of one year. Because we hypothesized the effects to take place across half a year, the last two waves were not included in the analyses presented here. First, a sample of 14,714 potential respondents was drawn from a representative omnibus survey in Germany (ADM master sample), employing a random last-two-digit dialing procedure. In this CATI screening, 5,286 respondents agreed to participate in all following waves.

Wave 1 was completed by 3,278 respondents (response rate: 38%), Wave 2 by 2,448 respondents (attrition rate: 25%), and Wave 3 by 2,021 respondents (attrition rate: 17%). We filtered 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 who 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 1, diagonal). Finally, we also calculated the intra-class correlation coefficient, quantifying 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 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 to indicate how often they disclosed 10 different pieces of information on the Internet. 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. The first first-order factor subsumed financial and medical information, the second covered first and last name, the third included place of residence and street (including house number), the fourth email address and phone number, and the fifth contained 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 similarly captured with 10 items that measured the general appraisal of disclosing the same 10 pieces of information. Adhering to the principle of compatibility (Fishbein & 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.

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 1, above the diagonal).
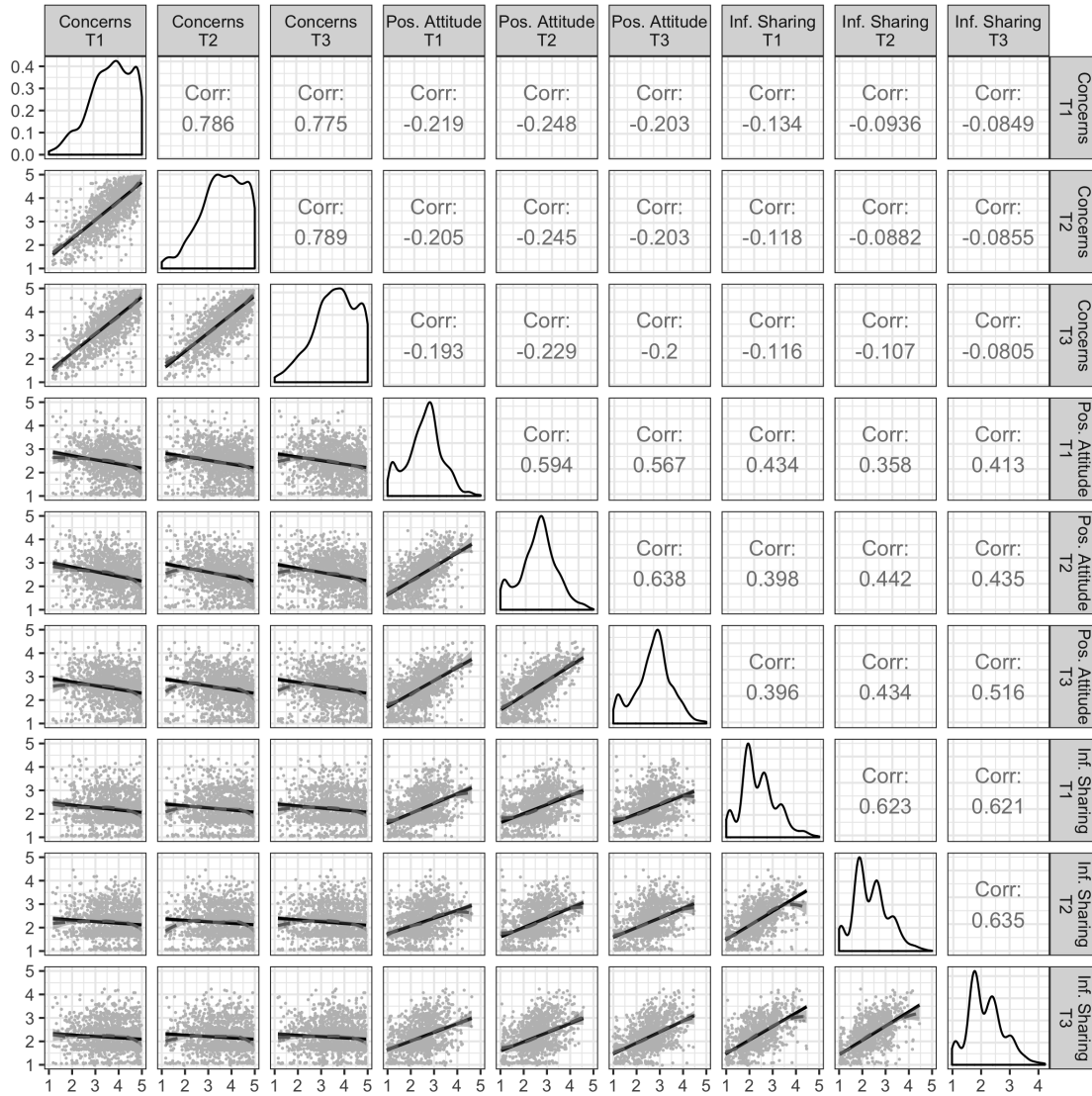
Figure 1. Results of the bivariate relations. Above the diagonal: zero-order correlation matrix; diagonal: density plots for each variable; below the diagonal: bivariate scatter plots for zero-order correlations. Solid regression lines represent linear regressions, dashed regression lines represent quadratic regressions. Calculated with the variables' latent factor scores.

405   Hypothesis 1 predicted that people reporting higher concerns about online privacy

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

407   Results revealed that the random intercepts of the two variables were significantly correlated

408   (β = -.09, b = -0.03, 95% CI [-0.05, -0.01], z = -2.57, p = .005). Respondents who—on

409 average across all three waves—were more concerned about their privacy than others also

410 shared slightly less personal information online. The effect was small. However, when

411 looking at the standardized effect's confidence interval (β = -.09, 95% CI [-.15, -.02]), it was

412 not significantly smaller than our SESOI of $beta$ = .10. Thus, Hypothesis 1 was supported.

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

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

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

416 [-0.03, > -0.01], z = -2.37, p = .009), suggesting that if respondents were more concerned

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

418 online at T1. In conclusion, the results supported Hypothesis 2.

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

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

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

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

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

424 revealing no significant effect (β = -.03, b = -0.03, 95% CI [-0.09, 0.04], z = -0.80, p = .422).

425   Hypothesis 3.1 predicted that people who perceived more privacy concerns than others

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

427 than others. The results revealed a medium-sized negative correlation between the two

428 variables on the between-person level (β = -.31, b = -0.11, 95% CI [-0.14, -0.08], z = -8.46, p

429 < .001). Thus, people who—on average across all three waves—reported being more

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

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

432 information, thereby supporting Hypothesis 3.1. Hypothesis 3.2 posited that people who

433 held more positive attitudes toward the online sharing of personal information than others

434 would also share more personal information online than others. Results showed a very strong

435 between-person correlation between the two variables (β = .66, b = 0.15, 95% CI [0.13, 0.17],

$z = 15.12$, $p < .001$): 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 ($\beta = -.06$, $b = -0.01$, 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 ($\beta = .15$, $b = 0.03$, 95% CI [0.02, 0.05], $z = 4.01$, $p < .001$),

indicating that when respondents had more positive attitudes toward the online sharing of

personal information at T1 than usual, they also shared more personal information online.

In conclusion, the results supported Hypothesis 4.2.

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

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

significant effect was found, $\beta = -.02$, $b = -0.02$, 95% CI [-0.09, 0.06], $z = -0.47$, $p = .641$.

Regarding Research Question 2.2, again no significant longitudinal relations emerged

between privacy attitudes and privacy concerns 6 months later $\beta < .01$, $b < 0.01$, 95% CI

[-0.06, 0.06], $z = 0.06$, $p = .951$.

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

personal information would affect changes in personal information sharing 6 months later.

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

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

information would affect attitudes toward the online sharing of personal information 6

months later. Again, no significant effect was found ($\beta = .04$, $b = 0.04$, 95% CI [-0.03, 0.11],

$z = 1.15$, $p = .249$).

463   Table 1 presents an overview of all results and the OSM presents additional

464 information and supplementary analyses (e.g., results of the RI-CLPM without

465 socio-demographic control variables or results of alternative multilevel regression models).

Discussion

467   Current research on the privacy paradox revealed that a significant relation between

468 concerns about online privacy and the online sharing of personal information exists and that

469 it is small (e.g., Baruh et al., 2017). However, whereas the theoretical premise of the privacy

470 paradox actually addresses a within-person effect, empirical studies have analyzed

471 between-person relations. On the basis of a representative sample of the German population,

472 from which three waves of data separated by 6 months were collected, we have hence

473 analyzed the privacy paradox by differentiating general between-person relations, short-term

474 within-person relations, as well as long-term within-person effects.

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

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

477 frequently. In addition, people who were more concerned about their privacy than others

478 also held substantially more negative attitudes toward disclosing personal information online.

479 Notably, we found a very strong between-person correlation between attitudes toward

480 information sharing and actual information sharing, implying that typical online disclosure

481 can be precisely predicted by a person's attitude. Taken together, the cross-sectional results

482 are in line with the extant literature: Specifically, the between-person correlation of privacy

483 concerns and information sharing found in this study (i.e., β = -.08) fell within the 95%

484 confidence interval of the effect reported by Baruh et al (i.e., r = -.13, 95% CI [-.07, -.18];

485 2017). Note that the between-person correlations reported here represent averaged

486 measurements across three waves, thereby rendering the findings comparatively robust. In

487 conclusion, this study replicates the finding that the privacy paradox does not seem to exist

488 on a between-person level: The differences between people with regard to their online

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 3 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 he or she usually is, he or she also shared less information than usual.

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 within-person results showed that when a person's privacy concerns increased, the same person also shared slightly less information online than he or she usually did. Moreover, we found that people who developed more positive attitudes toward sharing personal information online than usual also shared substantially more personal information online. In conclusion, the results suggest that changes in concerns and attitudes are both partially related to changes in behavior, implying that the privacy paradox does not seem to exist also on a within-person level.

Turning to the potential long-term effects of privacy concerns, the effects that we found were both theoretically negligible and statistically nonsignificant.

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. 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 (cf., Keijsers, 2016). Moreover, given that the directions of most longitudinal relations were in line with the between-person and within-person relations, it might be the case that longitudinal effects do indeed take place, but only that they are very small. Finally, it could also be that longterm longitudinal effects simply do not exist.

Limitations

As a major point of criticism, one can argue that some of the effect sizes reported in this study are only small, too small to refute the privacy paradox. On the one had, they could simply 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, one should indeed not overestimate the importance of privacy concerns; the impact on the online sharing of personal information could be larger, and other variables also play a role.

The study relied on estimations of information sharing that were based on self-reports. As has been shown before, people are not particularly good at estimating the frequency of behaviors that are part of their daily routines (Scharkow, 2016). Whenever possible, future studies should aim to combine self-reports of cognitions with 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 unfortunately were not yet aware of the importance of this practice.

Future Research

Although this is arguably the first study to demonstrate a within-person relation between concerns about online privacy and the online sharing of personal information, what is still missing is evidence of within-person longitudinal effects. The fact that we found significant within-person correlations at T1 but not across the 6-month intervals suggests that longitudinal effects do take place, but that a different time interval might be needed to uncover them. For theoretical reasons (e.g., due to availability heuristics), it would be plausible to use intervals that are shorter; for statistical reasons (e.g., because of the high stability of privacy concerns), however, it would even make sense to probe intervals that are longer (Dormann & Griffin, 2015).

Linking general personality traits with typical behavior, recent studies have analyzed the privacy paradox by taking an aggregate perspective. However, it seems important to analyze privacy behaviors from a situational perspective as well, one that accounts for temporal needs, interpersonal perceptions, contextual cues, or characteristics of

541 communication channels (Masur, 2018). For example, it might be the case that whereas

542 general levels of information sharing are best explained by using privacy *concerns*, situational

543 information sharing might be best explained using privacy *heuristics*, which are less energy

544 consuming and more situational (cf., Sundar, Kang, Wu, Gu, & Zhang, 2013).

545   As a final note, the privacy paradox argues that privacy concerns do not reflect

546 whatsoever on the sharing of personal information online, which we view as a strong claim.

547 However, when a single study does not yield a significant result, it does not necessarily imply

548 a theoretical problem; instead, it could also be a statistical miss. Because when analyzing

549 the privacy paradox we are likely dealing with small effects (Baruh et al., 2017), and to be

550 able to reliably detect these effect we need large samples. In conclusion, we encourage

551 researchers to use statistical designs that allow for sufficient statistical power.

552 **Conclusion**

553   Taken together, one might ask: What's the big deal? Researchers have now come closer

554 to solving the privacy paradox, which is a problem that by producing studies with

555 non-significant results they have created themselves. Admittedly, there is some truth to this

556 statement. At the same time, it is not only researchers who have thought that the online

557 sharing of personal information is paradoxical—the public media have also often suggested

558 that people tend to use the Internet in a somewhat nonsensical or overtly risky way (e.g.,

559 Naughton, 2019). Hence, given the common interest and involvement in the privacy paradox,

560 providing the public with a scientific answer seems relevant.

561   Second, being able to show that online behaviors are not paradoxical has another

562 benefit: It suggests that online and offline behaviors are not ontologically different. In offline

563 contexts, as well, we find that concerns are not closely aligned with behaviors. For example,

564 although most people are concerned about their health, a considerable number of people are

565 nonetheless smokers. However, despite this discrepancy public agencies are aware that they

566 still need to foster concern about health. For example, in May 2016, the European Union

mandated that cigarette packages must display graphic warning labels; while stable in the

years before, sales of cigarettes in Germany in 2016 dropped by 6.3 billion units, equaling

7.7% (Bundesamt, 2017). Although this result is only a correlation, it suggests that

addressing concerns can have societal benefits. Therefore, proclaiming that the online

sharing of personal information is not paradoxical and that concerns about online privacy

matter might leverage both people's responsibility and their agency (see also Adjerid, Peer,

& Acquisti, 2018).

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

they also shared a little less personal information about themselves online, and if

respondents considered sharing personal information not to be a sensible idea, they disclosed

even less. Both this study and the majority of the extant literature do not support a

"privacy paradox"; instead, if anything, they suggest a "privacy orthodox".

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