How Do Like and Dislike Buttons Affect Communication? A Privacy Calculus Approach to Understanding Self-Disclosure Online in a One-Week Field Experiment

Abstract

According to the privacy calculus, both privacy concerns and expected gratifications explain self-disclosure online. So far, most findings were based on self-reports, and little is known about whether the privacy calculus can explain also observations of authentic behavior. Likewise, we still know comparatively little as to whether the privacy calculus can be influenced by the design of online websites, including for example popularity cues such as like and dislike buttons. To answer these questions, we ran a preregistered one-week field experiment. Participants were randomly distributed to three different websites, on which they could discuss a current political topic. The final sample consisted of 590 participants. Although the originally preregistered model could not be confirmed, the results showed that the privacy calculus variables predicted a considerable share of actual self-disclosure. The impact of popularity cues was negligible. In conclusion, the results indicate that self-disclosure online can be explained by privacy concerns and specific gratifications. This finding has several implications. For example, it provides further evidence against the privacy paradox.

Keywords: privacy calculus, self-disclosure, popularity cues, field experiment, structural equation modeling, preregistration

Word count: 6358

How Do Like and Dislike Buttons Affect Communication? A Privacy Calculus Approach to Understanding Self-Disclosure Online in a One-Week Field Experiment

Understanding why people disclose personal information online remains a critical question for both society and academic research. Originally, self-disclosure online was thought to be mostly erratic—for example, it was assumed that self-disclosure cannot be predicted by assessing people's personal beliefs, concerns, or standpoints. Most prominently, the privacy paradox stated that people self-disclose vast amounts of personal information online *despite* having substantial concerns about their privacy (Barnes, 2006; Taddicken & Jers, 2011).

Somewhat surprisingly, despite its popularity in the media (Radio, 2018) the privacy paradox has garnered little empirical support. A recent meta-analysis revealed that the correlation between privacy concerns and self-disclosure on SNS is r = -.13 (Baruh, Secinti, & Cemalcilar, 2017), which indicates that privacy concerns are indeed related to self-disclosure online.

Rather than further pursuing the privacy paradox, a large share of current day research hence posits that self-disclosure online can be explained—at least partly—by means of the so-called *privacy-calculus* (Krasnova, Spiekermann, Koroleva, & Hildebrand, 2010). Building on the work of Laufer and Wolfe (1977), the privacy calculus claims that both expected risks *and* expected benefits explain self-disclosure. Specifically, by operationalizing expected risks as privacy concerns, several studies have shown that experiencing greater privacy concerns is related to disclosing less information (Heirman, Walrave, & Ponnet, 2013; Koohikamali, French, & Kim, 2019).

However, although the privacy calculus has gained some momentum in academic research several important questions remain unanswered. First, we still know comparatively little about whether the privacy calculus can be replicated with actual behavioral data in an authentic long-term setting (Kokolakis, 2017). Thus far, most research supporting the privacy calculus has used either self-reports of behavior (e.g., Krasnova et al., 2010), vignette approaches (e.g., Bol et al., 2018), or one-shot experiments in the lab (e.g., Trepte, Scharkow, & Dienlin, 2020). However, all three of these approaches have reduced external validity. As a result, in this study we analyze actual information sharing behavior in an authentic online setting.

Second, current research on the privacy calculus is often criticized for not explicitly focusing on the deliberation process of self-disclosure. According to critics (e.g., Knijnenburg et al., 2017), showing that concerns and gratifications both correlate with self-disclosure is not evidence for any substantial or explicit weighing of pros and cons. We agree and in this study hence explicitly focus on the privacy deliberation process itself. Moreover, and on a more general level, we aim to gauge the usefulness of further extending the privacy calculus model by adding new variables such as privacy deliberation, trust, and self-disclosure self-efficacy.

Finally, because the privacy calculus does not take place in a vacuum, and because it is often argued that self-disclosure can be easilty triggered by external circumstances, we analyze whether the privacy calculus can be affected by the design of a website. Specifically, in this study we investigate whether *popularity cues* such as like and dislike buttons have the power to affect the privacy calculus and to foster self-disclosure.

To test our research questions, we conducted a preregistered online field experiment, drawing from a representative sample of the German population. Participants were randomly distributed to one of three different websites, which either included only a like button, both a like and a dislike button, or no buttons at all. Over the course of one week participants had the chance to discuss a topical issue (i.e., prevention of terrorist attacks in Germany). Afterward, they answered our follow-up questionnaire with items pertaining to the privacy calculus variables.

The Privacy Calculus

Being a primary means of regulating privacy (e.g., Masur, 2018), self-disclosure is our key variable of interest. There are two different understandings of self-disclosure in the literature: The first defines self-disclosure as *deliberate* acts of sharing truthful information about the self with others (Jourard, 1964). The second considers *all* acts of sharing information—whether active or passive, deliberate or unwitting—as self-disclosure, because each piece of information shared allows meaningful inferences to be made about a person (e.g., Watzlawick, Bavelas, Jackson, & O'Hanlon, 2011). In this paper we follow the latter approach, not least because recent years have vividly illustrated how it is possible to derive a plethora of insights about a person simply by analyzing his or her written communication (e.g., Kosinski, Stillwell, & Graepel, 2013). Moreover, independent from which position one chooses to adopt, it is possible to differentiate the content of self-disclosure into three different dimensions: breadth (i.e., number of topics covered), depth (i.e., intimacy of topics covered), and length (i.e., quantity of disclosure) (e.g., Omarzu, 2000). In this study we mainly focus on communication quantity, as we consider communication quantity to be a necessary precondition and hence valid proxy for self-disclosure.

Privacy concerns have been defined as follows: "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" [AUTHOR]. Previous research has found that people who are more concerned about their privacy than others are less inclined to share personal information (Baruh et al., 2017; Dienlin & Trepte, 2015; Heirman et al., 2013; Koohikamali et al., 2019).

H1: People are more likely to self-disclose on a website when they are less concerned about their privacy.

Although privacy concerns are related to self-disclosure, one can make the case that since most studies in the literature report only small effects, there should also be additional meaningful factors that contribute to explaining self-disclosure. Most prominently, it has been argued that people trade a loss of privacy for a gain in gratifications such as social capital, entertainment, information, or self-presentation (Ellison, Vitak, Steinfield, Gray, & Lampe, 2011; Taddicken & Jers, 2011). By now, a large body of research has found support for this hypothesis (e.g., Krasnova et al., 2010; Min & Kim, 2015; Trepte et al., 2017).

H2: People are more likely to self-disclose on a website when they obtain more gratifications from using the website.

In the current literature on the privacy calculus there still seems to be a shortage of studies that explicitly analyze the decision process of actively comparing the pros and cons of disclosing information, although this point of criticism has been leveled several times (e.g., Knijnenburg et al., 2017) and although other fields such as behavioral economics have long focused on the underlying problem (e.g., Zhu, Ou, van den Heuvel, & Liu, 2017). This criticism is justified. The observation that both experiencing privacy concerns and expecting gratifications are related to self-disclosure does not bit itself necessitate an explicit weighing process Hence, we argue that the research on the privacy calculus would benefit significantly from analyzing this decision process explicitly. Building on Omarzu (2000) and Altman (1976), we hence address a novel concept that might best be termed *privacy deliberation*, which we define as the extent to which individual people explicitly compare positive and negative potential outcomes before communicating with others.

On the one hand, it seems plausible that deliberating about one's privacy would dampen subsequent self-disclosure, because refraining from regular communication—the primary means of connecting with others—requires at least a minimum of active and hence deliberate restraint. On the other hand, deliberating about one's privacy might also increase self-disclosure, as after having actively deliberated about the potential consequences, a person concerned about his or her privacy might arrive at the conclusion that in this situation self-disclosure is not only appropriate but expedient. In light of the paucity of empirical studies and the plausibility of both effects, we formulate the following research question:

RQ1: Are people more or less likely to self-disclose on a website when they more actively deliberate about whether they should self-disclose?

Several attempts have already been made to expand the privacy calculus (e.g., Dinev & Hart, 2006). Additional variables such as self-efficacy or trust have been introduced. Self-efficacy in the context of the privacy calculus captures whether people believe in their own capability to implement particular privacy behaviors in the future (Dienlin & Metzger, 2016). These privacy behaviors can either refer to self-withdrawal (e.g., deleting inappropriate content) or self-disclosure (e.g., publishing a blog post). Thus far, several studies have found that people who report more privacy self-efficacy also self-withdraw more online than others (e.g., Chen, 2018). In light of our focus on self-disclosure, in this study we investigate the influence of self-disclosure self-efficacy.

Trust can be conceptualized in two different ways (Gefen, Karahanna, & Straub, 2003): It either captures "*specific* beliefs dealing primarily with the integrity, benevolence, and ability of another party" (Gefen et al., 2003, p. 55, emphasis added) or a "*general* belief that another party can be trusted" (Gefen et al., 2003, p. 55, emphasis added). Whereas specific trust beliefs focus on the causes of trust, general trust beliefs focus on the experience of trust. Gefen et al. (2003) prioritize specific trust beliefs (p. 60). In the online context, it is important to differentiate among several targets of trust (Söllner, Hoffmann, & Leimeister, 2016). Potential targets include (a) the information system, (b) the provider, (c) the Internet, and (d) the community of other users (Söllner et al., 2016). Trust plays a key role in online communication (Metzger, 2004). For example, it has been demonstrated that people who put more trust in the providers of networks also disclose more personal information (Li, 2011).

In conclusion, while we expect to find these relations as well, we would also like to determine whether the inclusion of all the other variables mentioned above, including the not yet researched concept of privacy deliberation, might potentially attenuate or even obviate the predictive capacity of self-efficacy and trust.

H3: People are more likely to self-disclose on a website when their self-efficacy about self-disclosing on the website is higher.

H4: People are more likely to self-disclose on a website when they have greater trust in the provider, the website, and the other users.

The Effect of Popularity Cues

What is the effect of the communication context on the privacy calculus and on self-disclosure? First, it has often been noted that researchers should not exclusively focus on specific features of particular websites, for features are prone to change and quickly become obsolete (Fox & McEwan, 2017). Instead, it has been suggested that researchers prioritize underlying latent structures, for example by analyzing what are know as affordances (e.g., Ellison & Vitak, 2015; Fox & McEwan, 2017). The concept of affordances was developed by Gibson (2015), who argued that it is not the objective features of objects that determine behavior but rather subjective perceptions. Affordances are a mental representation of how a given entity might be used; as such, they are by definition subjective. There is much debate in the literature concerning what exactly defines an affordance (Evans, Pearce, Vitak, & Treem, 2017). For example, whereas Evans et al. (2017) propose three affordances for mediated communication (i.e., anonymity, persistence, and visibility), Fox and McEwan (2017) suggest 10 affordances for SNSs alone (i.e., accessibility, bandwidth, social presence, privacy, network association, personalization, persistence, editability, conversation control, and anonymity).

As the privacy calculus states that both benefits and costs determine behavior, we suggest that popularity cues such as like and dislike buttons, which are categorized as "paralinguistic digital affordances" (Carr, Hayes, & Sumner, 2018, p. 142), perfectly epitomize benefits and costs. The like button is positive; it expresses an endorsement, a compliment, a reward (Carr et al., 2018; Sumner, Ruge-Jones, & Alcorn, 2017). However, communication online is also often characterized by negative and critical debates (Ziegele, Weber, Quiring, & Breiner, 2017). As the dislike button is a major means of downgrading content it represents the cost and risk factor of the privacy calculus well. In fact, its stark negative effect might also explain why to date only a handful of major websites have implemented it (e.g., youtube, reddit or stackexchange).

Paralinguistic digital affordances and/or popularity cues have been shown to impact behavior (Krämer & Schäwel, 2020; Trepte et al., 2020). For example, a large-scale field experiment in which 101,281 comments were analyzed found that comments with dislikes were more likely to receive further dislikes (Muchnik, Aral, & Taylor, 2013). Stroud, Muddiman, and Scacco (2017) demonstrated that when users had a different opinion than the one that was communicated in a post, they were more likely to click on a button labelled *respect* compared to a button labelled *like*.

In this vein it seems plausible that popularity cues might also impact the privacy calculus [kramerMasteringChallengeBalancing2020]. First, on a primordial level, popularity cues serve as a means of reward and punishment, affecting behavior via instrumental conditioning (Skinner, 2014). Specifically, being complimented with a like should encourage future self-disclosure, while being punished with a dislike should inhibit future disclosure. Similarly, like buttons should be associated with being able to garner positive feedback, so implementing a like-button—similar to a compliment in the offline world—might leverage gratifications. Implementing a like or a dislike button might also bring people to more actively deliberate about whether or not it is actually worthwhile to disclose information. If both like and dislike buttons are present, privacy deliberation should increase even further. Finally, because people who are more concerned about their privacy are also more shy and risk averse (Dienlin, 2017), implementation of the dislike button should both stir privacy concerns and stifle self-disclosure. For a simplified overview of our theoretical model, see Figure 1.

H5. Compared to people who use a website without like or dislike buttons, people who use a website with like buttons (a) self-disclose more, (b) obtain more gratifications, (c) are less concerned about their privacy, and (d) deliberate more about whether they should communicate online.

H6. Compared to people who use a website without like or dislike buttons, people who use a website with like and dislike buttons (a) self-disclose more, (b) obtain more gratifications, and (c) deliberate more about whether they should communicate online.

H7. Compared to people who use a website with only like buttons, people who use a website with like and dislike buttons (a) are more concerned about their privacy, and (b) deliberate more about whether they should communicate online.

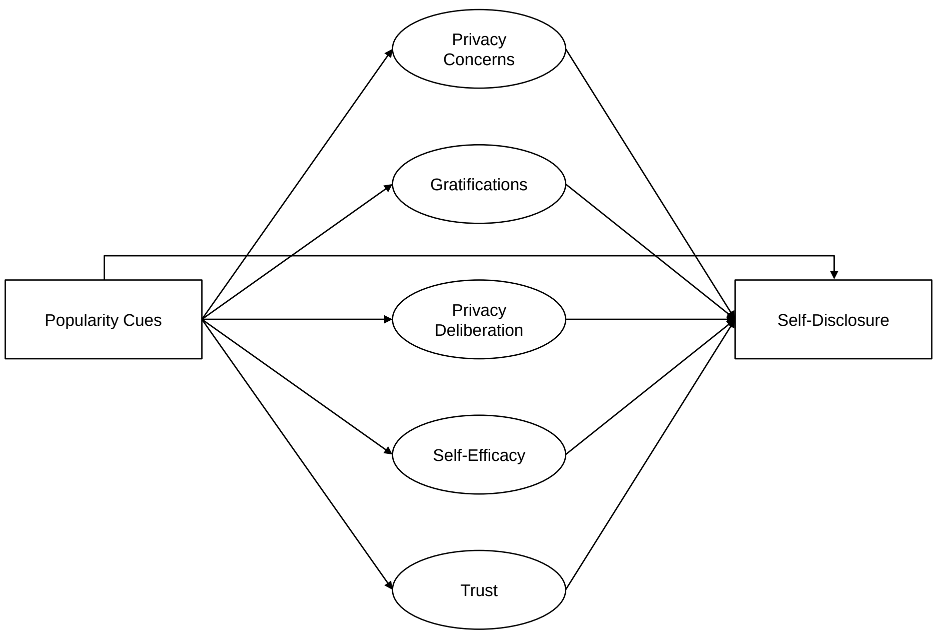


Figure 1. Overview of theoretical model.

Methods

Open Science

The online supplementary material (OSM) of this study include the data, research material, analyses scripts, and a reproducible version of this manuscript (see https://osf.io/hcqat/?view_only=5db35868738d40609b11e58cc343a9b0) We preregistered the study using the registration form *OSF Prereg*, which includes hypotheses, sample size, materials, analyses, and exclusion criteria (see https://osf.io/a6tzc/?view_only=5d0ef9fe5e1745878cd1b19273cdf859). We needed to change our pre-defined plan in some cases. For a full account of all changes, see OSM. New analyses that were not preregistered appear in the section on exploratory analyses. For example, we also measured two additional variables that were not included in the preregistration (e.g., *specific* gratifications and *general* trust; see below), which are included in the exploratory analyses.

Procedure

The study was designed as an online field experiment with three different groups. The first group interacted with a website without like/dislike buttons, the second with a website with only like buttons, and the third with a website with both like and dislike buttons. Participants were randomly distributed to one of the three websites in a between-subject design.

We collaborated with a professional panel agency to recruit participants. As incentive, participants were awarded digital points, which they could use to get special offers from other companies. Participants were above the age of 18 and lived in Germany. In a first step, the agency sent their panel members an invitation to participate in the study (*invitation*). In this invitation, panel members were asked to participate in a study analyzing the current threat posed by terrorist attacks in Germany.[1] Members who decided

[1] Although the terror attack was not of primary interest for this study, the data can and will also be used

to take part were subsequently sent the first questionnaire (*T1*), in which we asked about their sociodemographics, provided more details about the study, and included a registration link for the website. Afterward, participants were randomly assigned to one of the three websites. After registration participants had the chance to discuss the topic of the terrorism threat in Germany over the course of one week (*field*). Subsequently, participants received a follow-up questionnaire in which we collected the self-reported measures (*T2*). Measures were collected after and not before the field phase in order not to prime participants or reveal our primary research interest.

We programmed an online website based on the open-source software discourse (https://www.discourse.org/). We conducted several pretests with students from the local university to make sure the website had an authentic feel (see Figure 2). Participants used the website actively: Overall, they spent 9,694 minutes online, wrote 1,171 comments, and left 560 popularity cues. For an example of communication that took place, see Figure 3.

Participants

We ran a priori power analyses to determine how many participants to recruit. The power analysis was based on the smallest effect size of interest (SESOI; Lakens, Scheel, & Isager, 2018). Thus, we defined an effect size that we would consider enough to support our hypotheses. Because small effects should be expected when researching aspects of privacy online (e.g., Baruh et al., 2017), with small effects beginning at an effect size of $r = .10$ (Cohen, 1992), we set our SESOI to be r = .10. Our aim was to be able to detect this SESOI with a probability of at least 95%. Using the regular alpha level of 5%, this leads to a minimum sample size of $n = 1{,}077$. In the end, we were able to include n = 561 in our analyses (see below). This means that our study had a probability (power) of 77% of finding an effect at least as large as $r = .10$. Put differently, we were able to make reliable

to analyze perceptions of the terrorism threat. Hence, no deception took place, and in the debriefing participants were informed about our additional research interest in privacy.

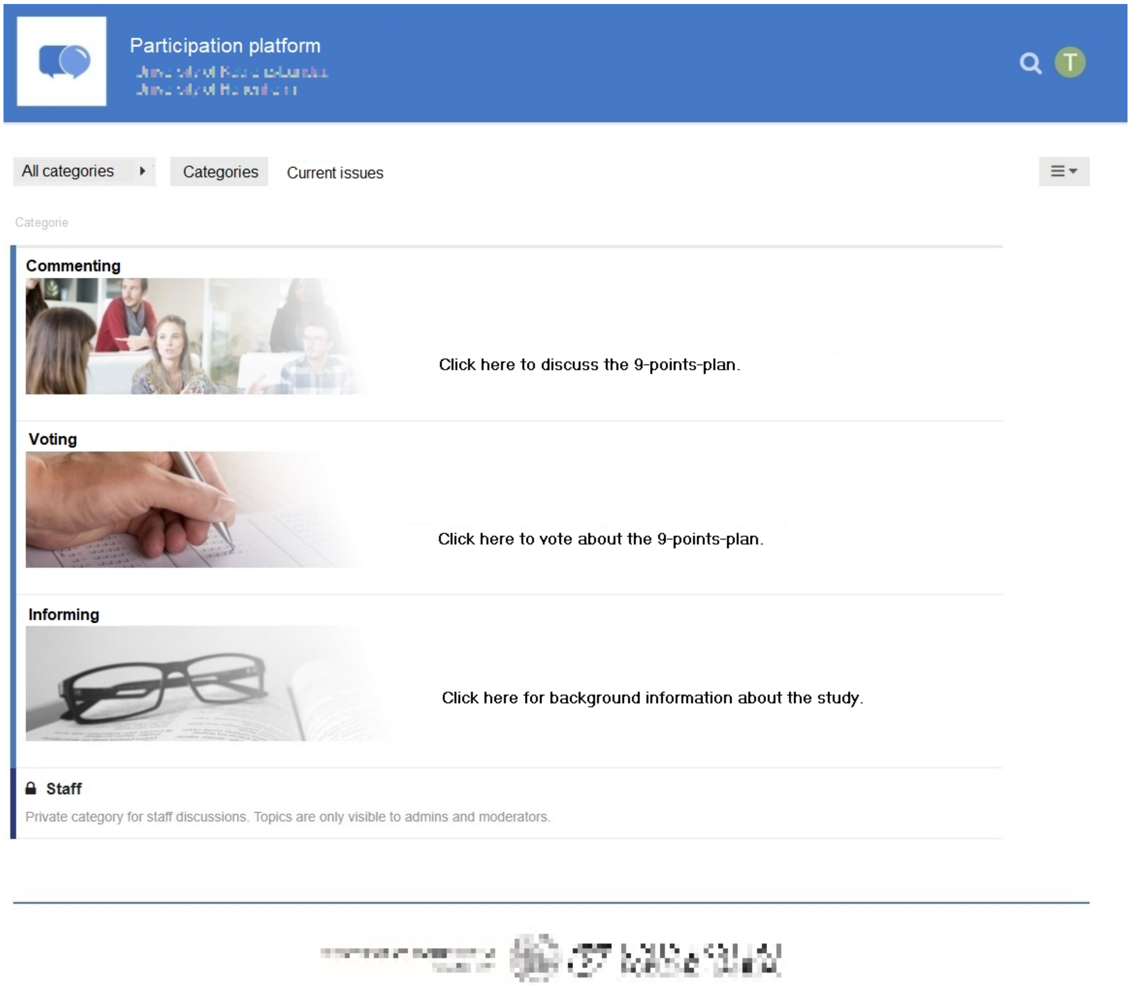


Figure 2. The website's homepage. (Translated to English; university logos pixelated for peer review.)

inferences about effects at least as big as $r = .14$.

We collected a representative sample of the German population in terms of age, sex, and federal state. 1,619 participants completed the survey at T1, 960 participants created a user account on the website, and 982 participants completed the survey at T2. Using tokens and IP addresses, we connected the data from T1, participants' behavior on the platform, and T2 by means of objective and automated processes. The data for $n = 590$ participants could be matched successfully across all three platforms. We excluded $n = 29$ participants who finished the questionnaire at T2 in less then three minutes, which we

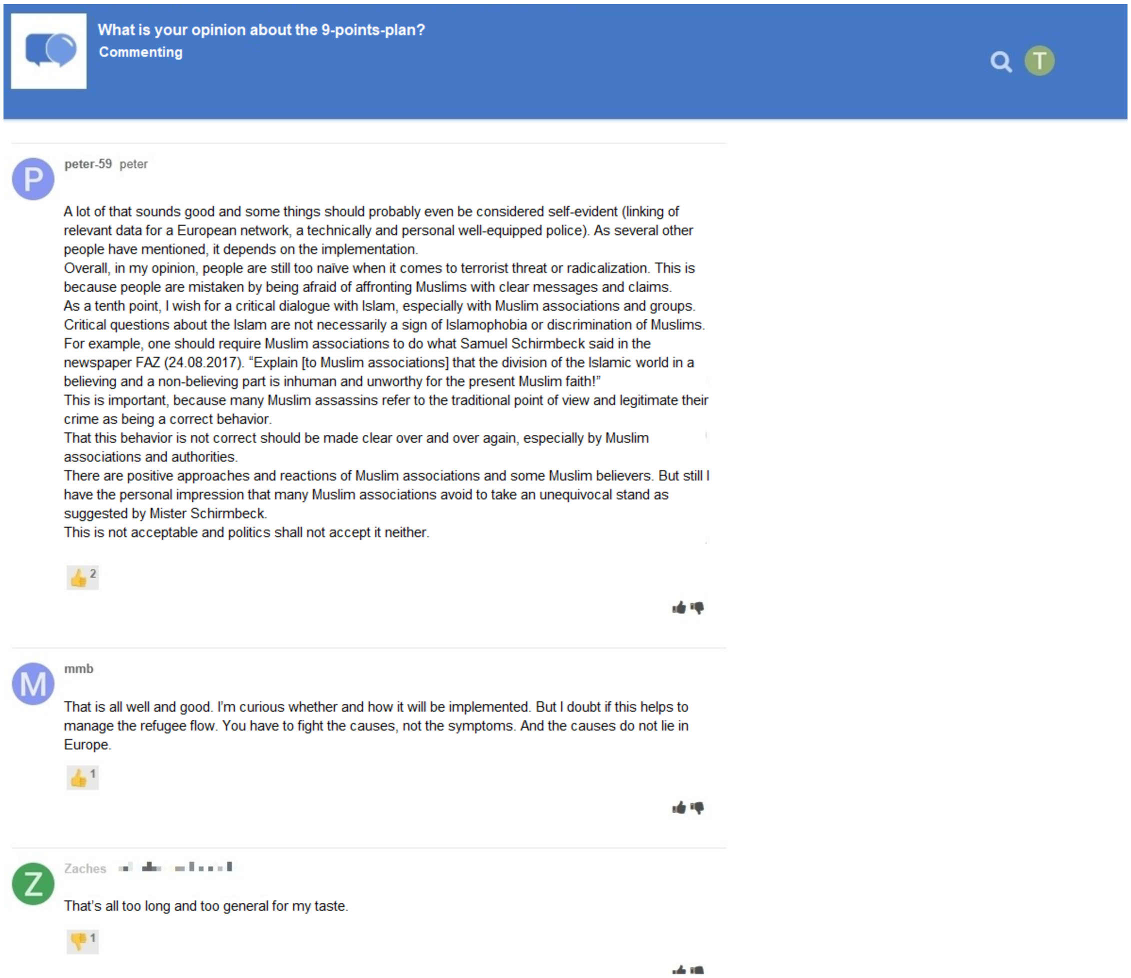


Figure 3. Communication that took place on the website with like and dislike buttons. (Translated to English.)

considered to be unreasonably fast. To detect corrupt data, we calculated Cook's distance. We excluded 2 participants because they provided clear response patterns. The final sample included 561 participants. The sample characteristics at T1 and T2 were as follows: T1: Age = 45 years, sex = 49% male, college degree = 22%. T2: Age = 46 years, sex = 49% male, college degree = 29.00%. (One participant did not report his or her sex.)

Measures

In what follows, we present the materials we used to measure our variables. Wherever possible, we operationalized our variables using established measures. Where impossible

Table 1

Psychometric Properties, Factorial Validity, and Reliability of Measures

	m	sd	chisq	df	pvalue	cfi	tli	rmsea	srmr	omega	ave
Privacy concerns	3.21	1.52	11.04	9.00	0.27	1.00	1.00	0.02	0.01	0.96	0.80
General gratifications	4.76	1.23	34.44	5.00	0.00	0.98	0.95	0.10	0.02	0.94	0.75
Specific gratifications	4.71	1.03	270.68	85.00	0.00	0.94	0.93	0.06	0.05	0.93	0.59
Privacy deliberation	3.93	1.29	14.88	5.00	0.01	0.98	0.96	0.06	0.02	0.85	0.54
Self-efficacy	5.24	1.12	2.21	1.00	0.14	1.00	0.98	0.05	0.01	0.86	0.60
General trust	5.20	1.05	1.64	1.00	0.20	1.00	1.00	0.03	0.01	0.87	0.70
Specific trust	5.07	0.95	77.29	26.00	0.00	0.97	0.95	0.06	0.04	0.92	0.62

Note. omega = Raykov's composite reliability coefficient omega; avevar = average variance extracted.

(for example, to date there exists no scale on privacy deliberation), we self-designed novel items that were pretested in terms of legibility and/or understandability. To gauge the variables' factor validity, we ran confirmatory factor analyses (CFA). If the CFAs revealed insufficient fit, we deleted individual items. All items were formulated as statements to which participants indicated their (dis-)agreement on a bipolar 7-point scale. Answer options were as follows: -3 (*strongly disagree*), -2 (*disagree*), -1 (*slightly disagree*), 0 (*neutral*), +1 (*slightly agree*), +2 (*agree*), +3 (*strongly agree*). In the questionnaire, all items measuring a variable were presented on the same page in a randomized order.

For an overview of the means, standard deviations, factorial validity, and reliability, see Table 1. For an overview of the variables' distributions, see Figure 4. For the exact wording of all items and their individual distributions, see OSM.

Privacy concerns. Privacy concerns were measured with seven items based on Buchanan, Paine, Joinson, and Reips (2007). One example item was "When using the participation platform, I had concerns about my privacy". One item had to be deleted due

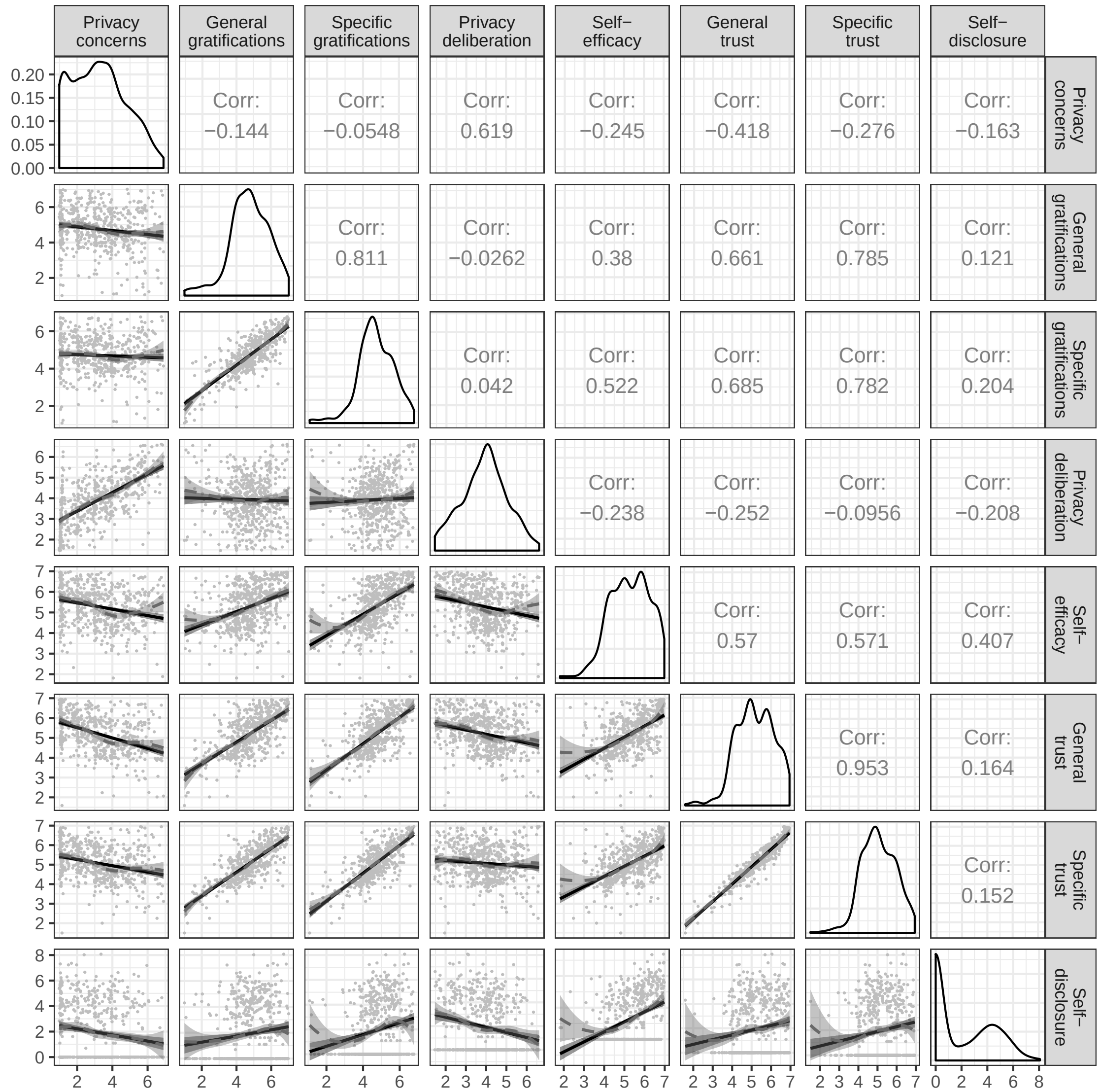


Figure 4. Above diagonal: zero-order correlation matrix; diagonal: density plots for each variable; below diagonal: bivariate scatter plots for zero-order correlations. Solid regression lines represent linear regressions, dotted regression lines represent quadratic regressions. Calculated with the model predicted values for each variable (baseline model).

to poor psychometric properties.

Gratifications. Next, we differentiated between two separate types of gratification. *General gratifications* were measured with five items based on Sun, Wang, Shen, and Zhang (2015). One example item was “Using the participation platform has paid off for me”.

Specific gratifications were measured with 15 items on five different subdimensions with three items each. The scaled was loosely based on Scherer and Schlütz (2002). Example items were: "Using the participation platform made it possible for me to" … "learn things I would not otherwise have noticed" (information), "react to a subject that is important to me" (relevance), "engage politically" (political participation), "try to improve society" (idealism), and "soothe my guilty consciences" (extrinsic benefits).

Privacy deliberation. Privacy deliberation was measured with 5 self-designed items. One example item was "While using the participation platform I have weighed the advantages and disadvantages of writing a comment."

Self-efficacy. Self-efficacy was captured with six self-designed items, which captured whether participants felt that they had sufficient self-efficacy to write a comment on the platform. For example, we asked "I felt technically competent enough to write a comment." Two items, which were inverted, had to be deleted due to poor psychometric properties.

Trust. Next, we differentiated between two separate types of trust. *General trust* was operationalized based on Söllner et al. (2016) for three targets (i.e., provider, website, and other users), with one item each. One example items was "The operators of the participation platform seemed trustworthy." *Specific trust* was operationalized for the same three targets with three subdimensions each (i.e., ability, benevolence/integrity, and reliability), which were measured with one item each. Example items were "The operators of the participation platform have done a good job" (ability), "The other users had good intentions" (benevolence/integrity), "The website worked well" (reliability). The results showed that the provider and website targets were not sufficiently distinctive, as was evidenced by the existence of a Heywood case. We hence adapted the scale to combine these two targets. The updated scale exhibited adequate fit.

Self-disclosure. Self-disclosure was calculated by taking the log scale of the number of words each participant wrote in a comment plus the number of likes and dislikes, with likes and dislikes being multiplied by two. Like and dislike buttons were multiplied by two because, rudimentarily, like buttons abbreviate the sentence “I like” and dislike buttons the sentence “I dislike”. The sum of words and likes/likes was log-scaled because the relative amount of self-disclosure diminishes the more a person has already said.

Data analysis

All hypotheses and research questions were tested using structural equation modeling (SEM). The influence of the three websites was analyzed using contrast coding, which allows for testing the effects of experimental manipulations within a theoretical framework using latent variables (e.g., Kline, 2016). Because the dependent variable (self-disclosure) was not normally distributed, we estimated the model using robust maximum likelihood (Kline, 2016). As recommended by Kline (2016), we report the following global fit indices: χ^2, RMSEA (90% CI), CFI, and SRMR. Because sociodemographic variables are often related to self-disclosure and other privacy-related variables (e.g., Dindia & Allen, 1992), we controlled all variables for the influence of sex, age, and education. Preregistered hypotheses were tested with a one-sided significance level of 5%. Research questions were tested with a two-sided 5% significance level using family-wise Bonferroni-Holm correction. Exploratory analyses were conducted from a descriptive perspective, and the reported p-values/CIs should not be overinterpreted.

We used R (Version 3.6.1; R Core Team, 2018) and the R-packages *lavaan* (Version 0.6.5; Rosseel, 2012), *papaja* (Version 0.1.0.9942; Aust & Barth, 2018), *pwr* (Version 1.2.2; Champely, 2018), *quanteda* (Version 1.5.2; Benoit, 2018), *semTools* (Version 0.5.2; Jorgensen et al., 2018), and *tidyverse* (Version 1.3.0; Wickham, 2017) for all our analyses.

Results

Descriptive Analyses

First, we measured and plotted all bivariate relations between the study variables (see Figure 4). The results did not reveal any relationships to be particularly curvilinear. Furthermore, all variables making up the privacy calculus demonstrated the expected relationships with self-disclosure. For example, people who were more concerned about their privacy had written fewer posts (r = -.16). Worth noting is that specific gratifications and general trust predicted self-disclosure better than general gratifications and specific trust. The mean of privacy deliberation was $m = 3.93$. Altogether, 32% of participants reported having actively deliberated about their privacy.

It is important to note that the bivariate results showed three very large correlations: First, between specific trust and general gratifications ($r = .78$); second, between privacy concerns and privacy deliberation ($r = .62$); third, between specific gratifications and self-efficacy ($r = .52$). As all six variables were later analyzed within a single multiple regression, problems of multicollinearity might occur.

Privacy Calculus

Preregistered analyses. First, we ran a model as specified in the preregistration. The model fit our data comparatively well, $\chi^2(388) = 953.45$, $p < .001$, cfi = .94, rmsea = .05, 90% CI [.05, .05], srmr = .05. Regarding H1, we did not find that general gratifications predicted self-disclosure (β = -.04, b = -0.06, 95% CI [-0.22, 0.09], z = -0.78, p = .217; one-sided). Regarding H2, neither did we find that privacy concerns predicted self-disclosure ($\beta = .07$, $b = 0.14$, 95% CI [-0.19, 0.47], $z = 0.84$, $p = .199$; one-sided). The analyses for RQ1 similarly revealed that privacy deliberation was not correlated with self-disclosure (β = -.10, b = -0.16, 95% CI [-0.34, 0.02], z = -1.72, p = .085; two-sided). With regard to H3, however, we found that experiencing self-efficacy predicted self-disclosure substantially ($\beta = .38$, $b = 0.78$, 95% CI [0.49, 1.07], $z = 5.29$, $p < .001$;

one-sided). Concerning H4, the results showed that trust was not associated with self-disclosure (β = -.12, b = -0.30, 95% CI [-0.83, 0.22], z = -1.13, p = .129; one-sided).

However, these results should be treated with caution. As mentioned above, we indeed detected problems related to multicollinearity. For example, in this multiple regression trust had a *negative* relation with self-disclosure, whereas in the bivariate analysis the relation was *positive*. "Wrong" signs are a typical indicator of multicollinearity (Grewal, Cote, & Baumgartner, 2004).

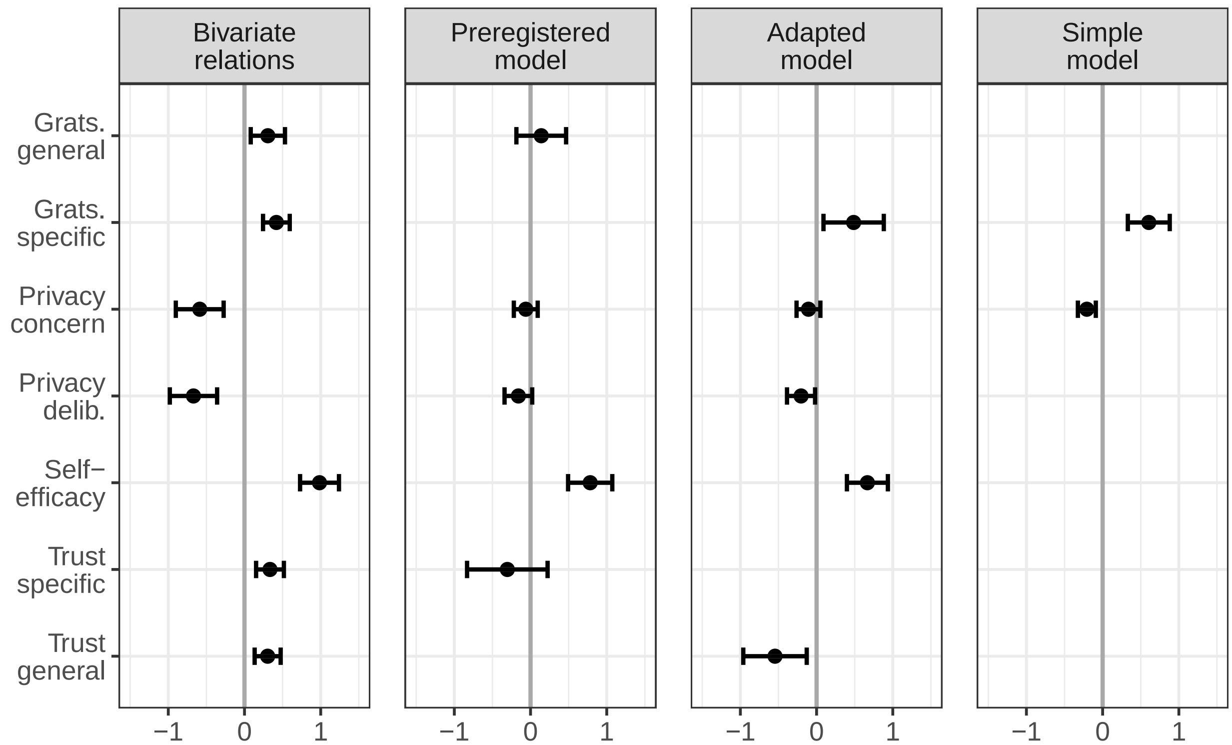
Exploratory analyses. Thus, we slightly adapted our preregistered model on the basis of the insights described above. First, instead of specific trust and general gratifications we now included general trust and specific gratifications, which were correlated slightly less strongly with one another. The adapted model fit our data comparatively well, $\chi^2(507) = 1502.61$, $p < .001$, cfi = .93, rmsea = .06, 90% CI [.06, .06], srmr = .06.

In the adapted privacy calculus model, we found that specific gratifications were positively related to self-disclosure online (β = .17, b = 0.49, 95% CI [0.09, 0.88], z = 2.41, p = .016). Furthermore, people who deliberated more about their privacy disclosed less information (β = -.13, b = -0.20, 95% CI [-0.39, -0.02], z = -2.17, p = .030). Self-efficacy remained substantially correlated with self-disclosure (β = .33, b = 0.67, 95% CI [0.40, 0.94], z = 4.86, $p < .001$). However, we again found a negative correlation between trust and self-disclosure (β = -.19, b = -0.55, 95% CI [-0.96, -0.13], z = -2.57, p = .010), which again implies multicollinearity.

When confronted with multicollinearity, two responses are typically recommended (Grewal et al., 2004): (a) combining collinear variables into a single measure, or (b) keeping only one of the collinear variables. Combining variables was not an option in our case, because both trust and expected benefits are theoretically distinct constructs. Because several variables were closely related to one another, in the end we therefore decided to fit a simple privacy calculus model, which contains only privacy concerns and specific gratifications.

The simple model fit our data well, $\chi^2(202) = 717.70$, $p < .001$, cfi = .95, rmsea = .07, 90% CI [.06, .07], srmr = .05. First, we found that people who experienced more privacy concerns than others disclosed less information (β = -.15, b = -0.21, 95% CI [-0.32, -0.09], z = -3.46, $p < .001$). Second, people who reported more specific gratifications than others self-disclosed more information (β = .21, b = 0.61, 95% CI [0.33, 0.88], z = 4.32, $p < .001$). Both effect sizes were above our predefined SESOI of r = .10, implying that the effects were sufficiently large to be relevant. For a visual overview of all results, see Figure .

\begin{figure}[!h]



\caption{Predictors of self-disclosure. Displayed are the 95% CIs of the unstandardized effects.} \end{figure}

When comparing the three models with one another, the simple privacy calculus model was the most parsimonious one (BIC = 37,292, AIC = 36,691), followed by the preregistered model (BIC = 48,949, AIC = 48,097), and the adapted model (BIC = 57,686, AIC = 56,716).

Popularity Cues

Preregistered analyses. In a next step, we analyzed the potential effects of the popularity cues on the privacy calculus. Somewhat surprisingly, we found no effects of the popularity cues on the privacy calculus variables. For an illustration, see Figure 5, which displays the model-predicted values for each variable (using the baseline model) and shows that the confidence intervals of all preregistered variables overlap. For the results of the specific inference tests using contrasts, see the OSM.

Exploratory analyses. The picture remained mostly the same also when analyzing variables that we did not include in the preregistration. Note that some differences missed statistical significance only marginally (e.g., specific gratifications for the comparison between the website with like buttons and the control website without like and dislike buttons). Nevertheless, we refrain from reading too much into the differences between the three websites and conclude that they were mostly similar regarding the privacy calculus variables and the amount of self-disclosure.

Discussion

In this study, we analyzed the privacy calculus using actual observed behavior in a preregistered field experiment. We additionally asked whether the privacy calculus is affected by popularity cues such as like and dislike buttons. The data came from a representative sample of the German population and were analyzed using structural equation modeling.

In the bivariate analyses, all privacy calculus variables were shown to significantly predict self-disclosure. In the preregistered analyses using multiple regression, in which several variables were analyzed together, self-efficacy was the strongest predictor of self-disclosure. All other variables were not significant, which is why the originally postulated extended privacy calculus model was not supported by the data. However, this preregistered model exhibited significant problems typical of multicollinearity, which is why

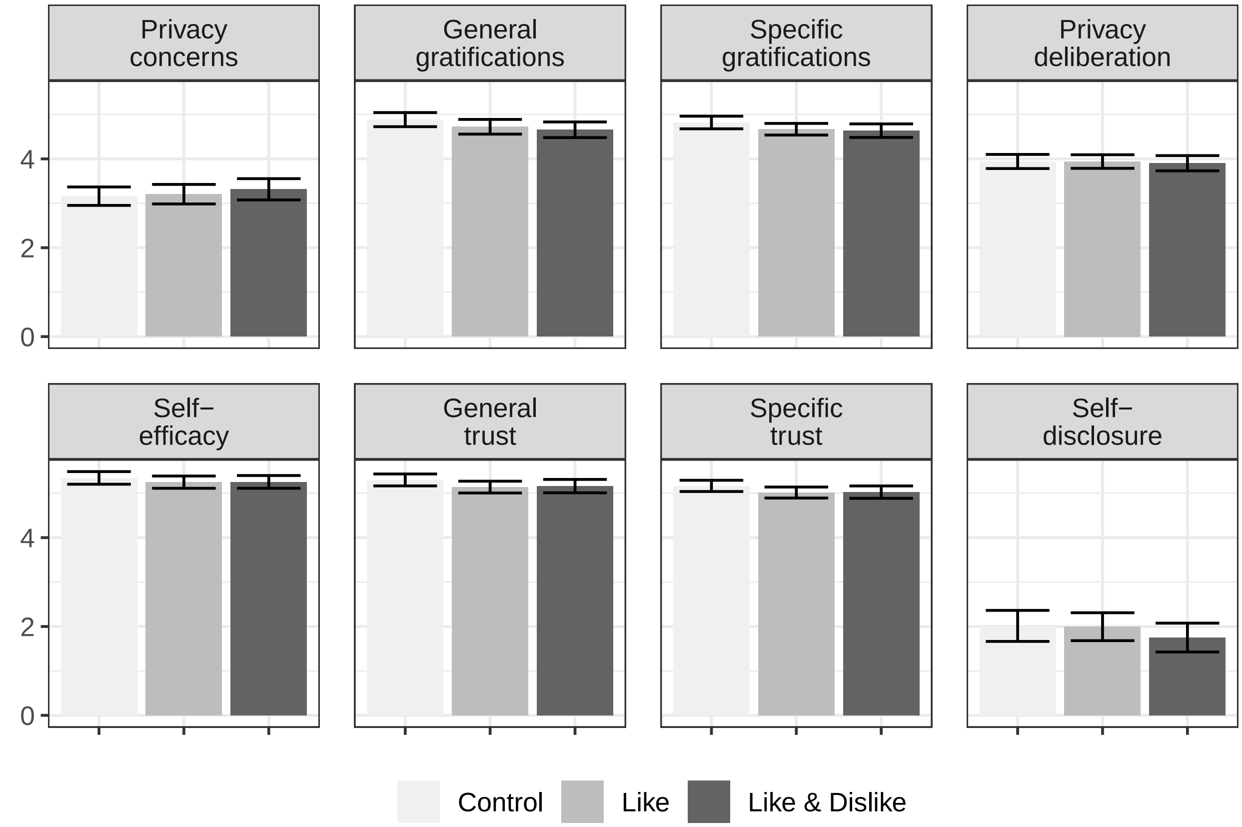


Figure 5. Overview of the variables for the three websites. Control: Website without buttons. Like: Website with like buttons. Like & Dislike: Website with like and dislike buttons.

we also explored (a) an adapted version of the preregistered model, in which we exchanged two variables, and (b) a more basal privacy calculus model, which included only privacy concerns and specific gratifications.

The adapted model suggests that also when holding all other variables constant, people who deliberate more about their privacy share less, people who expect more specific gratifications disclose more, and people who feel more self-efficacious disclose more. However, the model also suggests that if trust increases, while all other factors remain constant, self-disclosure decreases, which seems implausible. As a result, we also fit the above-mentioned simple privacy calculus model, which showed that both privacy concerns and obtained gratifications significantly and meaningfully predicted self-disclosure. Taken together, the results support the privacy calculus framework and suggest that self-disclosure online is not erratic and that it can be explained by various psychological variables.

Relatedly, the results suggest that in new communication contexts roughly one third of all Internet users actively deliberates about their privacy. Determining whether this figure is large or small is a normative question. For example, one can convincingly argue that this number should be higher and that we as society should still more actively deliberate about our self-disclosure practices online. Interestingly, results showed that privacy deliberation and privacy concerns were remarkably similar, which was evidenced by their strong correlation with one another and their comparable correlations with other variables. This either implies that thinking about one's privacy increases one's concern or, conversely, that being concerned about one's privacy leads one to think about one's options more actively. Future research might tell.

The next major implication is that several scenarios and uses cases exist in which popularity cues do not seem to have an overly strong influence on the privacy calculus and self-disclosure. Although some studies have found that popularity cues substantially impact behavior (e.g., Muchnik et al., 2013), in our study we found the opposite: Users still disclosed the same amount of personal information regardless of whether or not a website included like or dislike buttons, potentially highlighting the agency of users.

The results also have several more fine-grained implications. First, we question the tendency to further increase the complexity of the privacy calculus model by adding additional variables (e.g., Dienlin & Metzger, 2016). "Since all models are wrong the scientist cannot obtain a"correct" one by excessive elaboration. [...] Just as the ability to devise simple but evocative models is the signature of the great scientist so overelaboration and overparameterization is often the mark of mediocrity" (Box, 1976, p. 792). Specifically, we have come to believe that adding self-efficacy to privacy calculus models is of limited value, for self-efficacy is mostly a self-reported proxy of behavior and offers little epistemic insight. Instead, it might be more interesting to find out *why* some people feel sufficiently efficacious to self-disclose whereas others do not. In addition, although adding variables increases the amount of explained variance, it introduces further problems, for example spurious results due to multicollinearity.

In general, we think that the topic of multicollinearity should receive more scholarly attention. Interestingly, one can rightfully argue that multicollinearity is not actually a problem, but rather a warning sign. From a *statistical* perspective, when predictors are strongly correlated this only means that standard errors increase (Vanhove, 2019). In other words, when predictors are strongly correlated we can be less certain about the effects we obtain, because there is less variance (Vanhove, 2019). So to increase certainty researchers could compensate by collecting larger samples, which would allow to achieve sufficient statistical power. Fortunately, using accessible statistical software it is now possible to run a priori power analyses that explicitly account for correlated/collinear predictors (Wang & Rhemtulla, 2020).

From a *theoretical* perspective, multicollinearity could also suggest that the underlying theoretical model is ill-configured. It is our understanding that multiple regression is often used with the aim to isolate effects, to make sure that effects are not simply caused by another third variable. However, in cases of highly correlated measures this often does not make much sense theoretically. For example, in our case combining trust and gratification asks how increasing benefits affects self-disclosure, *while holding trust constant*. Theoretically, however, it is more plausible to assume that increasing gratifications also fosters trust (Söllner et al., 2016). In the preregistered analysis we even went further and tested whether trust increases self-disclose while holding constant several variables such as gratifications, privacy concerns, privacy deliberations, and self-efficacy, measures which are all strongly correlated. In short, the effects we found could even be correct, but the interpretation is much more difficult, artificial, and thereby of little theoretical and practical value.

Furthermore, we found a remarkably strong correlation between specific trust and expected gratifications (i.e., $r = .79$). At first glance, this strong relation seemed somewhat peculiar to us. On closer inspection, however, we realized that the way trust is routinely operationalized in the literature is very close to expected gratifications. To illustrate, the trust subdimension *ability* includes items such as "The comments of other users were useful". In fact, in the literature trust is often operationalized as a formative construct that directly results from factors such as expected benefits (Söllner et al., 2016). In conclusion, our results suggest that we should not confuse *causes* of trust with *measures* of trust, for this might introduce problems of both homogeneity and/or multicollinearity. Instead, we recommend to measures general and reflective measures of trust, which are less closely related to expected gratifications.

Limitations

The results do not allow for causal interpretation on the within-person level. First, all results are based on analyses of between-person variance. However, between-person relations often do not translate well to within-person effects (e.g. Hamaker, Kuiper, & Grasman, 2015). While some studies on privacy concerns online have begun to examine both sources of variance (e.g., Dietvorst, Hiemstra, Hillegers, & Keijsers, 2017), finding that intrapersonal changes in privacy concerns are indeed related to intrapersonal changes in self-disclosure, similar analyses are still lacking for the privacy calculus.

Second, the self-reported measures were collected *after* the field phase in which the dependent variable was measured. As a result, the coefficients might overestimate the actual relations, because demand effects might have led participants to artificially align their theoretical answers with their practical behavior to reduce dissonance. Nevertheless, we deliberately decided to measure the self-reported variables afterward in order to not bias participants and not prime our specific research interest.

Third, in experiments we should manipulate only the experimental variable while holding all others constant. In this study, we explicitly manipulated the popularity cues. However, as the experiment was conducted in the field, several other variables could not be held constant; for example, the content of communication by other users, the unfolding communication dynamics, or the characteristics of other users. As a result, the assumption of stable unit treatment was violated (Kline, 2016).

It is important to note that our not having found significant effects of like and dislike buttons does not necessarily mean that like and dislike buttons do indeed have no effect on self-disclosure and the privacy calculus. As always, with null-findings one is confronted with the *Duhème-Quinn Problem* (Dienes, 2008), which—put somewhat crudely—states that null findings can either be due to an actual non-existence of effects or, instead, to a poor operationalization of the research question. In this case, we were not able send participants notifications when their comments were liked/disliked, which significantly decreases the popularity cues' salience.

This paper analyzes self-disclosure in the context of political participation. Our focus was on understanding self-disclosure, which is why we deliberately excluded variables pertaining to political participation, such as informational self-efficacy (Loy, Masur, Schmitt, & Mothes, 2018). Moreover, operationalizing self-disclosure via communication quantity is, of course, only a proxy. Notably, we did not find any instances of people providing meaningless text and, as mentioned above, in times of big data, every piece of communication allows for increasingly accurate inferences about one's personality.

Conclusion

While some scholars discuss whether we should wish "Death to the privacy calculus?" (Knijnenburg et al., 2017, p. 1), in our opinion the privacy calculus is alive and kicking. This study adds to the growing confirmation of observation that people who are more concerned about their privacy than others disclose less information online, whereas people who receive more gratifications from using a website than others disclose more information online. The results of this study suggest that a substantial share of internet users, approximately 30%, consciously engage in a privacy calculus by actively deliberating about whether or not to disclose information. The results thereby provide further evidence against the privacy paradox. Popularity cues such as like and dislike buttons seem to play only a minor role in this process, especially if no means are implemented to guarantee that users are notified about others liking or disliking their communication. In conclusion, our results indicate that internet users are at least somewhat proactive and reasonable—probably no more or less proactive or reasonable than in any other regular everyday situation.

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