1 How Do Like and Dislike Buttons Affect Communication? A Privacy Calculus Approach to

2 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, little is known about whether the privacy calculus can be used to predict observations of actual authentic behavior, and whether the privacy calculus can be influenced by the design of online websites—for example, by implementing popularity cues such as like and dislike buttons. To answer this question, we ran a preregistered one-week field experiment, in which participants were randomly distributed to three different websites where they could discuss a current political topic. First, the results showed that privacy calculus variables predicted a considerable share of actual self-disclosure. Second, we found that the impact of implementing popularity cues was negligible. In conclusion, the results demonstrate that self-disclosure online can be explained by, for example, privacy concerns and psychological gratifications. This finding has several implications—for example, it provides further evidence against the privacy paradox.

For a preprint of the manuscript, the data, syntax, and additional analyses, see https://osf.io/hcqat/?view_only=5db35868738d40609b11e58cc343a9b0. Please note that in order to improve readibility, we deliberately placed figures and tables in the running text and not at the end.

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

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), indicating that privacy concerns are indeed related to self-disclosure
online.

Rather than further pursuing the privacy paradox, a large share of current day
research posits that self-disclosure online can be explained—at least partly—by means of
the so-called *privacy-calculus* (Krasnova, Spiekermann, Koroleva, & Hildebrand, 2010).
The privacy calculus builds on the work of Laufer & Wolfe (1977) and 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 (e.g.,
Heirman, Walrave, & Ponnet, 2013).

However, although the privacy calculus has gained some momentum 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

50 al., 2018), or one-shot experiments in the lab (e.g., Trepte, Scharkow, & Dienlin, 2020).

51 However, all three of these approaches significantly hamper external validity.

52   Second, current research on the privacy calculus is often criticized for not explicitly

53 focusing on the deliberation process of self-disclosure. According to critics (e.g.,

54 Knijnenburg et al., 2017), showing that concerns and gratifications both correlate with

55 self-disclosure is not evidence for any substantial or explicit weighing of pros and cons. We

56 agree and consider it necessary to now explicitly focus on the privacy deliberation process

57 itself. Moreover, and on a more general level, we aim to gauge the usefulness of further

58 extending the privacy calculus model by adding new variables such as privacy deliberation,

59 trust, and self-disclosure self-efficacy.

60   Finally, we want to determine whether the privacy calculus can be affected by the

61 design of a website. Specifically, we analyze whether *popularity cues* such as like and dislike

62 buttons affect self-disclosure and the privacy calculus.

63   To test our research questions, we conducted a preregistered online field experiment,

64 drawing from a representative sample of the German population. Participants were

65 randomly distributed to one of three different websites, which either featured only a like

66 button, both a like and a dislike button, or no buttons at all. Over the course of one week

67 participants had the chance to discuss a topical issue (i.e., prevention of terrorist attacks in

68 Germany). Afterward, they answered our follow-up questionnaire with items pertaining to

69 the privacy calculus variables.

The Privacy Calculus

71   Being a primary means of regulating privacy (e.g., Masur, 2018), self-disclosure is our

72 key variable of interest. There are two different understandings of self-disclosure in the

73 literature: The first defines self-disclosure as *deliberate* acts of sharing truthful information

74 about the self with others (Jourard, 1964). The second considers *all* acts of sharing

75 information—whether active or passive, deliberate or unwitting—as self-disclosure, because

76 each piece of information shared allows meaningful inferences to be made about a person

77 (e.g., Watzlawick, Bavelas, Jackson, & O'Hanlon, 2011). In this paper we follow the latter

78 approach, not least because recent years have vividly illustrated how it is possible to derive

79 a plethora of insights about a person simply by analyzing his or her written communication

80 (e.g., Kosinski, Stillwell, & Graepel, 2013). Moreover, independently from which position

81 one chooses to adopt, it is possible to differentiate the content of self-disclosure into three

82 different dimensions: breadth (i.e., number of topics covered), depth (i.e., intimacy of

83 topics covered), and length (i.e., quantity of disclosure) (e.g., Omarzu, 2000). In this study

84 we mainly focus on communication quantity, as we consider communication quantity to be

85 a necessary precondition and hence valid proxy for self-disclosure.

86 Privacy concerns have been defined as follows: "Concerns about online privacy

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

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

89 accompanied by an uneasy feeling that his or her privacy might be threatened"

90 [AUTHOR]. Previous research has found that people who are more concerned about their

91 privacy than others are less inclined to share personal information (e.g., Baruh et al., 2017;

92 Dienlin & Trepte, 2015; Heirman et al., 2013).

93 H1: People are more likely to self-disclose on a website when they are less concerned

94 about their privacy.

95 Although privacy concerns are related to self-disclosure, one can make the case that

96 since most studies in the literature report only small effects, there should also be additional

97 meaningful factors that contribute to explaining self-disclosure. Most prominently, it has

98 been argued that people trade a loss of privacy for a gain in gratifications such as social

99 capital, entertainment, information, or self-presentation (Ellison, Vitak, Steinfield, Gray, &

100 Lampe, 2011; Taddicken & Jers, 2011). By now, a large body of research has found support

101 for this hypothesis (e.g., Krasnova et al., 2010; Min & Kim, 2015; Trepte et al., 2017).

102 H2: People are more likely to self-disclose on a website when they obtain more

103 gratifications from using the website.

104 In the current literature on the privacy calculus there still seems to be a shortage of

105 studies that explicitly analyze the process of actively comparing the pros and cons of

106 disclosing information, even though this point of criticism has been levelled several times

107 (e.g., Knijnenburg et al., 2017) and even though other fields such as behavioral economics

108 have long focused on the underlying problem (e.g., Zhu, Ou, van den Heuvel, & Liu, 2017).

109 The criticism is justified, because showing that experiencing privacy concerns and

110 expecting gratifications are related to self-disclosure does not necessarily imply that an

111 explicit weighing took place. Hence, we argue that research on the privacy calculus would

112 benefit significantly from addressing a novel concept that might best be termed *privacy*

113 *deliberation*, which we define as the extent to which individual people explicitly compare

114 positive and negative potential outcomes before communicating with others.

115 On the one hand, it seems plausible to suggest that deliberating about one's privacy

116 would dampen subsequent self-disclosure, because refraining from regular

117 communication—the primary means of connecting with others—requires at least a

118 minimum of active and hence deliberate restraint. On the other hand, deliberating about

119 one's privacy might also increase self-disclosure, as after having actively deliberated about

120 the potential consequences, a person concerned about his or her privacy might arrive at the

121 conclusion that in this situation self-disclosure is not only appropriate but expedient. In

122 light of the paucity of studies and the plausibility of both effects, we formulate the

123 following research question:

124 RQ1: Are people more or less likely to self-disclose on a website when they more

125 actively deliberate about whether they should self-disclose?

126 Several attempts have already been made to expand the privacy calculus (e.g., Dinev

127 & Hart, 2006). Additional variables such as privacy self-efficacy or trust have been

128 introduced. Building on Dienlin & Metzger (2016), self-efficacy in the context of the

129 privacy calculus captures whether people believe in their own capability to implement

particular privacy behaviors in the future that foster either 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).

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) or a "general belief that another party can be trusted" (Gefen et al., 2003, p. 55). 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). For example, one can differentiate between (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 (e.g., Metzger, 2004). For example, it has been demonstrated that people who put more trust in the providers of networks also disclose more personal information (see, e.g., 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

156 on specific features of particular websites, for features are prone to change and quickly

157 become obsolete (Fox & McEwan, 2017). Instead, it has been suggested that researchers

158 prioritize underlying latent structures, for example by analyzing what are know as

159 affordances (e.g., Ellison & Vitak, 2015; Fox & McEwan, 2017). The concept of affordances

160 was developed by Gibson (2015), who argued that it is not the objective features of objects

161 that determine behavior but rather subjective perceptions. Affordances are a mental

162 representation of how a given entity might be used; as such, they are by definition

163 subjective. There is much debate in the literature concerning what exactly defines an

164 affordance (Evans, Pearce, Vitak, & Treem, 2017). For example, whereas Evans et al.

165 (2017) propose three affordances for mediated communication (i.e., anonymity, persistence,

166 and visibility), Fox & McEwan (2017) suggest 10 affordances for SNSs alone (i.e.,

167 accessibility, bandwidth, social presence, privacy, network association, personalization,

168 persistence, editability, conversation control, and anonymity).

169   As the privacy calculus states that both benefits and costs determine behavior, we

170 suggest that popularity cues such as like and dislike buttons, which are categorized as

171 "paralinguistic digital affordances" (Carr, Hayes, & Sumner, 2018, p. 142), perfectly

172 epitomize benefits and costs. The like button is positive; it expresses an endorsement, a

173 compliment, a reward (e.g., Sumner, Ruge-Jones, & Alcorn, 2017). However,

174 communication online is also often characterized by negative and critical debates (e.g.,

175 Ziegele, Weber, Quiring, & Breiner, 2017). As the dislike button is a major means of

176 downgrading content it represents the cost and risk factor of the privacy calculus well—in

177 fact, its stark negative effect might also explain why only a handful of major websites have

178 implemented a dislike button (e.g., reddit.com or stackexchange.com).

179   Popularity cues have been shown to impact behavior. For example, a large-scale field

180 experiment in which 101,281 comments were analyzed found that comments with dislikes

181 were more likely to receive further dislikes (Muchnik, Aral, & Taylor, 2013). Stroud,

182 Muddiman, & Scacco (2017) demonstrated that when users had a different opinion than

183 the one that was communicated in a post, they were more likely to click on a button

184 labelled *respect* compared to a button labelled *like.*

185   In this vein it seems plausible to suggest that popularity cues might also impact the

186 privacy calculus. First, on a very primordial level, popularity cues should serve as a means

187 of reward and punishment, as a mechanism of instrumental conditioning (Skinner, 2014).

188 Specifically, we argue that being complimented with a like should encourage future

189 self-disclosure, while being punished with a dislike should inhibit future disclosure.

190 Similarly, like buttons should be associated with being able to garner positive feedback, so

191 implementing a like-button—similar to a compliment in the offline world—might leverage

192 gratifications. Implementing a like or a dislike button might also bring people to more

193 actively deliberate about whether or not it is actually worthwhile to disclose information.

194 If both like and dislike buttons are present, privacy deliberation should increase even

195 further. Finally, because people who are more concerned about their privacy are also more

196 shy and risk averse (Dienlin, 2017), implementation of the dislike button should both stir

197 privacy concerns and stifle self-disclosure. For a simplified overview of our theoretical

198 model, see Figure 1.

199   H5. Compared to people who use a website without like or dislike buttons, people

200 who use a website with like buttons (a) self-disclose more, (b) obtain more gratifications,

201 (c) are less concerned about their privacy, and (d) deliberate more about whether they

202 should communicate online.

203   H6. Compared to people who use a website without like or dislike buttons, people

204 who use a website with like and dislike buttons (a) self-disclose more, (b) obtain more

205 gratifications, and (c) deliberate more about whether they should communicate online.

206   H7. Compared to people who use a website with only like buttons, people who use a

207 website with like and dislike buttons (a) are more concerned about their privacy, and (b)

208 deliberate more about whether they should communicate online.

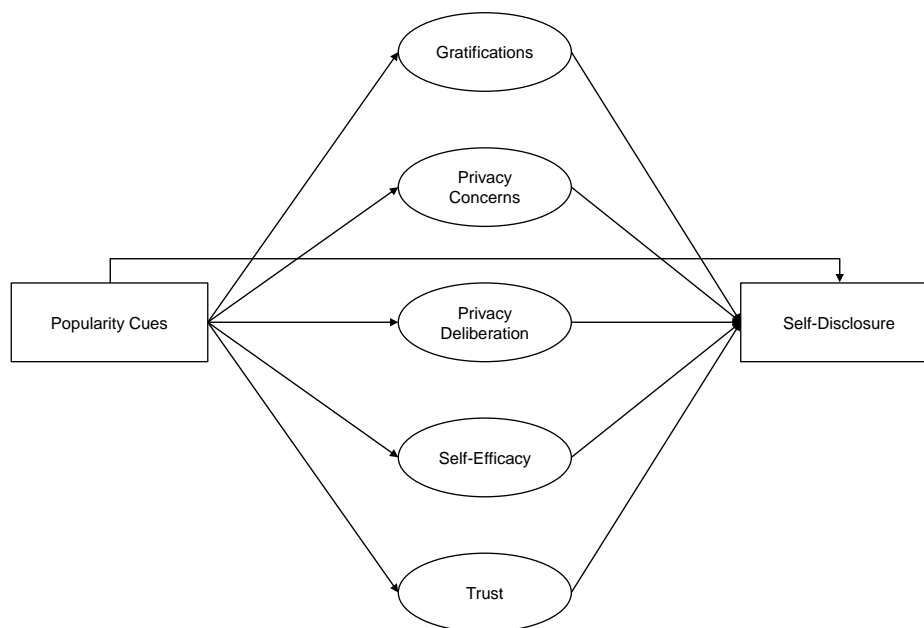*Figure 1*. Overview of theoretical model.

<h1 style="text-align:center">Methods</h1>

Open Science

We preregistered the study's hypotheses, sample size, materials, analyses, and

exclusion criteria (see

https://osf.io/a6tzc/?view_only=5d0ef9fe5e1745878cd1b19273cdf859[1]). We needed to

change our pre-defined plan in some cases. For a full account of all changes, see online

supplementary material (OSM),

https://osf.io/hcqat/?view_only=5db35868738d40609b11e58cc343a9b0. New analyses that

were not preregistered appear in the section on exploratory analyses. For example, we also

measured additional variables that were not included in the preregistration (e.g., specific

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[1] To find the actual preregistration on the website, click *View Registration Form* (blue button on the right hand side).

²¹⁹ gratifications and general trust; see below), whose results we report as exploratory analyses.

Procedure

²²¹   The study was designed as an online field experiment with three different groups.
²²² The first group interacted with a website without like/dislike buttons, the second with a
²²³ website with only like buttons, and the third with a website with both like and dislike
²²⁴ buttons. Participants were randomly distributed to one of the three websites in a
²²⁵ between-subject design.

²²⁶   We collaborated with a professional panel agency to recruit participants. As an
²²⁷ incentive, participants were awarded digital points, which they could use to get special
²²⁸ offers from other companies. In order to be able to take part, participants needed to be
²²⁹ above the age of 18 and had to live in Germany. In a first step, the agency sent their panel
²³⁰ members an invitation to participate in the study (*invitation*). In this invitation, panel
²³¹ members were asked whether they would be interested in taking part in a study analyzing
²³² the threat posed by current terrorist attacks in Germany.[2] If panel members decided to
²³³ take part, they were subsequently sent the first questionnaire (*T1*) in which we asked
²³⁴ about the participants' sociodemographics, provided more details about the study, and
²³⁵ included a registration link for the website. Afterward, the participants were randomly
²³⁶ assigned to one of the three websites. After registration participants had the chance to
²³⁷ discuss the topic of the terrorism threat in Germany over the course of one week (*field*).
²³⁸ Afterward, participants received a follow-up questionnaire in which we collected the
²³⁹ self-reported measures (*T2*). Measures were collected after and not before the field phase
²⁴⁰ in order not to prime participants or reveal our primary research interest.

²⁴¹   We programmed an online website based on the open-source software discourse

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

242 (https://www.discourse.org/). We conducted several pretests with students from the local

243 university to make sure the website had an authentic feel (see Figure 2). Participants used

244 the website actively: Overall, users spent 9929 minutes online and wrote 1208 comments

245 (for an example of communication that took place, see Figure 3).
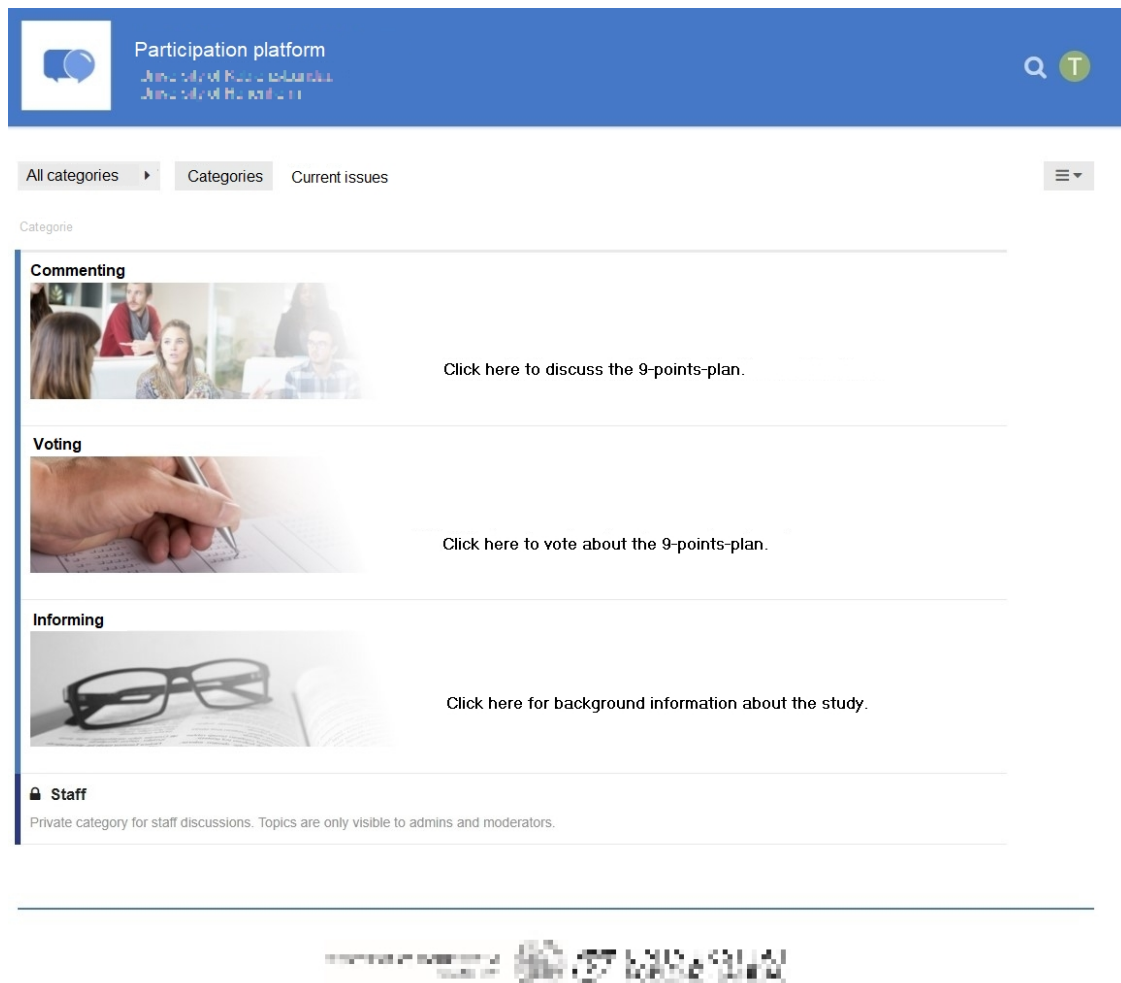

Figure 2. The website's homepage. (Translated to English; university logos pixelated for peer review.)

246 **Participants**

247   We ran a priori power analyses to determine how many participants to recruit. The

248 power analysis was based on the smallest effect size of interest (SESOI; Lakens, Scheel, &

249 Isager, 2018). Thus, we defined an effect size that we would consider enough to support our
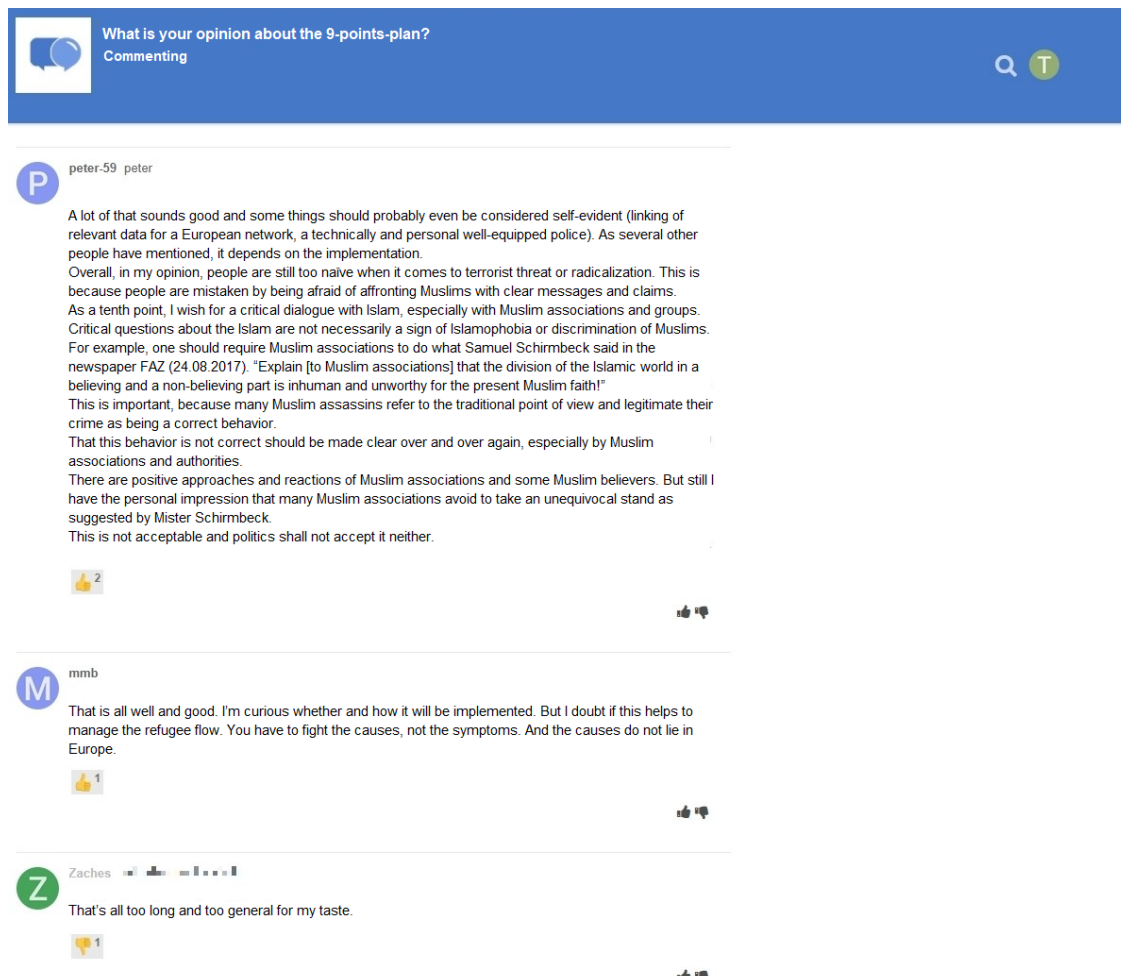
Figure 3. Communication that took place on the website with like and dislike buttons. (Translated to English.)

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 = 0.10. 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 $n = 1077$. In the end, we were able to include n = 528 in our analyses (see below). This means that our study had a probability (power) of 74% of finding an effect at least as large as $r = 0.10$. Put differently, we were able to make reliable inferences about effects at least as big as $r = 0.14$.

We collected a representative sample of the German population in terms of age, sex,

and federal state. T1 was completed by $N = 1412$ participants and T2 by $n = 996$ participants. We connected the data from T1, participants' behavior on the platform, and T2 by means of objective and automated processes (e.g., participants were matched via tokens or IP addresses). So far, we have been able to match the data for $n = 528$ participants. The matching process is not yet finished, and we will try to match the remaining cases manually. We excluded $n = 27$ participants who finished the questionnaire at T2 in less then three minutes, which we considered to be unreasonably fast. The sample characteristics at T1 were as follows: Age = 46 years, sex = 49% male. The sample characteristics of T2 were as follows: Age = 46 years, sex = 49% male. Hence, despite dropout, T2 can also be considered a largely representative sample of the German population.

Measures

In what follows, we present the materials we used to measure our variables. 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 the OSM.

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

Table 1

Psychometric Properties, Factorial Validity, and Reliability of Measures

	m	sd	chisq	df	pvalue	cfi	tli	rmsea	srmr	omega	ave
Privacy concerns	3.19	1.51	41.91	9.00	0.00	0.99	0.98	0.08	0.01	0.96	0.80
General gratifications	4.76	1.22	46.01	5.00	0.00	0.98	0.96	0.12	0.02	0.94	0.75
Specific gratifications	4.71	1.00	448.03	85.00	0.00	0.93	0.91	0.09	0.06	0.93	0.58
Privacy deliberation	3.91	1.31	22.39	5.00	0.00	0.98	0.97	0.08	0.02	0.85	0.55
Self-efficacy	5.26	1.11	56.66	8.00	0.00	0.97	0.94	0.11	0.03	0.85	0.62
General trust	5.20	1.06	0.00	0.00	NA	1.00	1.00	0.00	0.00	0.87	0.71
Specific trust	5.07	0.94	122.11	24.00	0.00	0.97	0.95	0.09	0.03	0.92	0.61

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

Gratifications. Next, we differentiated between two separate types of gratification. *General gratifications* were measured with five items based on Sun, Wang, Shen, & 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 & 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).

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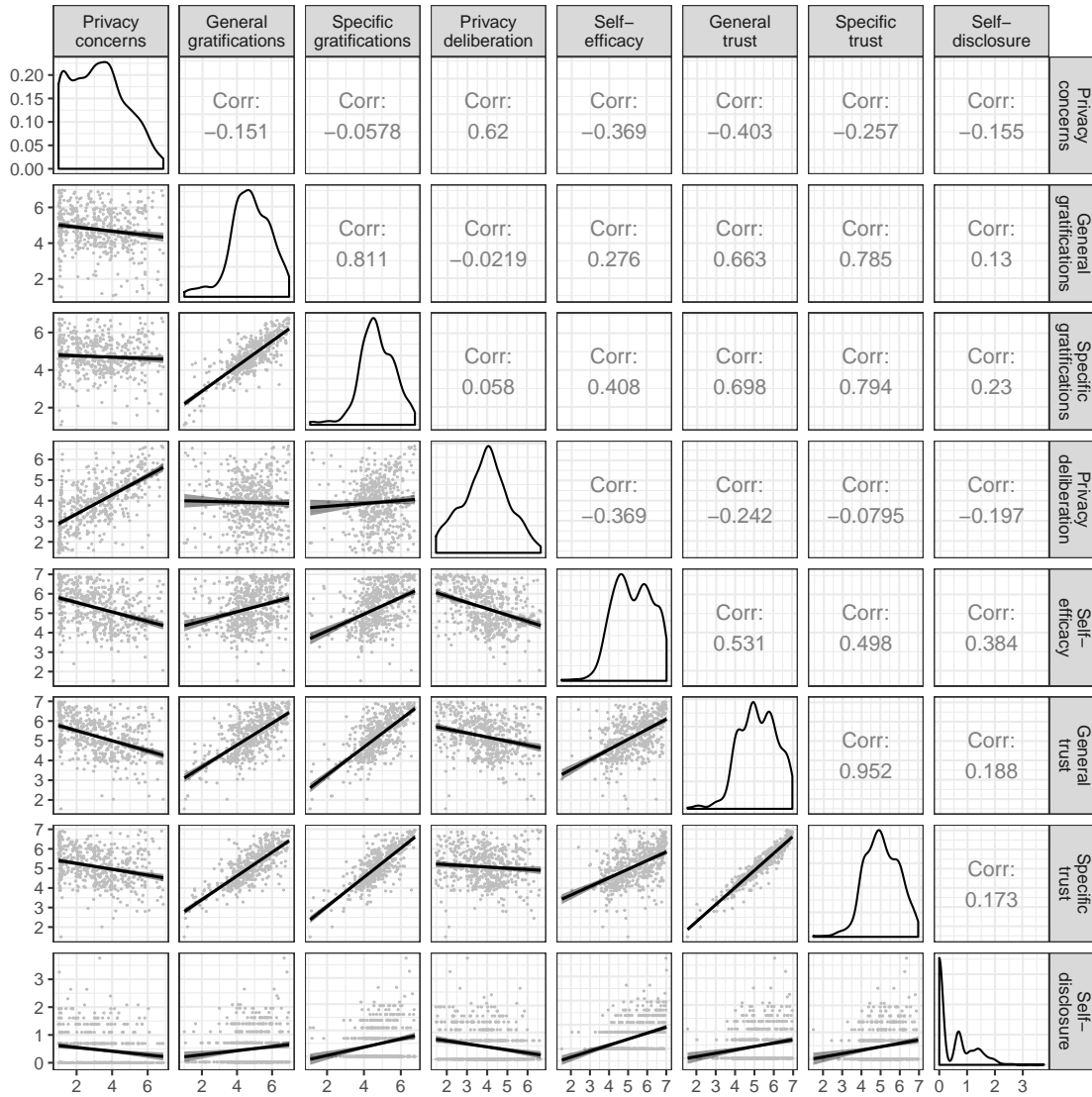
Figure 4. Above diagonal: zero-order correlation matrix; diagonal: density plots for each variable; below diagonal: bivariate scatter plots for zero-order correlations. Solid regression lines represent linear regressions, dotted regression lines represent quadratic regressions. Calculated with the model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

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.

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-disclosure.   Self-disclosure was calculated by taking the natural logarithm of

the number of comments each participant posted.

Data analysis

We tested all hypotheses and research questions using structural equation modeling

(SEM). We tested the influence of the three websites using contrast coding, which allows

for testing the effects of experimental manipulations within a theoretical framework using

latent variables (e.g., Kline, 2016). As 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. As sociodemagraphic 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 and age. Preregistered hypotheses were

tested with a one-sided significance level of 5%. Research questions and exploratory

analyses were tested with a two-sided 5% significance level using family-wise

Bonferroni-Holm correction. We used R (Version 3.6.1; R Core Team, 2018) and the

R-packages *lavaan* (Version 0.6.5; Rosseel, 2012), *papaja* (Version 0.1.0.9842; Aust &

329 Barth, 2018), *pwr* (Version 1.2.2; Champely, 2018), *quanteda* (Version 1.5.2; Benoit, 2018),

330 *semTools* (Version 0.5.2; Jorgensen et al., 2018), and *tidyverse* (Version 1.3.0; Wickham,

331 2017) for all our analyses.

Results

Descriptive Analyses

334   First, we measured and plotted all bivariate relations between the study variables

335 (see Figure 4). The results did not reveal any relationships to be particularly curvilinear.

336 Furthermore, all variables making up the privacy calculus demonstrated the expected

337 relationships with self-disclosure. For example, people who were more concerned about

338 their privacy had written fewer posts ($r = $ -.15). Worth noting is that specific gratifications

339 and general trust predicted self-disclosure better than general gratifications and specific

340 trust. The mean of privacy deliberation was $m = 3.91$. Altogether, 32% of participants

341 reported having actively deliberated about their privacy.

342   It is important to note that the bivariate results showed three very large correlations:

343 First, between specific trust and general gratifications ($r = 0.79$); second, between privacy

344 concerns and privacy deliberation ($r = 0.62$); third, between specific gratifications and

345 self-efficacy ($r = 0.41$). As all six variables were later analyzed within a single multiple

346 regression, problems of multicollinearity might occur.

Privacy Calculus

348   **Preregistered analyses.** First, we ran a model as specified in the preregistration.

349 The model fit our data comparatively well, $\chi^2(389) = 1202.15$, $p < .001$, cfi $= .93$, rmsea $=$

350 .06, 90% CI [.06, .07], srmr $= .05$. Regarding H1, we did not find that general gratifications

351 predicted self-disclosure ($\beta = $ -.04, $b = $ -0.02, 95% CI [-0.06, 0.03], $z = $ -0.64, $p = .262$).

352 Regarding H2, neither did we find that privacy concerns predicted self-disclosure ($\beta = .07$,

353 $b = 0.04$, 95% CI [-0.05, 0.13], $z = 0.84$, $p = .201$). The analyses for RQ1 similarly revealed

354 that privacy deliberation was not correlated with self-disclosure (β = -.09, b = -0.04, 95%

355 CI [-0.10, 0.02], z = -1.33, p = .184). With regard to H3, however, we found that

356 experiencing self-efficacy substantially predicted self-disclosure (β = .36, b = 0.21, 95% CI

357 [0.13, 0.29], z = 5.31, p < .001). Concerning H4, the results showed that trust was not

358 associated with self-disclosure (β = -.09, b = -0.06, 95% CI [-0.20, 0.07], z = -0.92, p =

359 .179).

360   However, these results should be treated with utmost caution. As mentioned above,

361 we indeed detected problems suggesting multicollinearity. Most prominently, in this

362 multiple regression trust had a negative relation with self-disclosure, even though when

363 analyzed bivariately the relation was positive—which is a sign of multicollinearity (Kline,

364 2016). As a result, specific trust and general gratifications should not be analyzed within

365 the same model, as the two concepts are empirically too close to one another.

366   **Exploratory analyses.**   Thus, we slightly adapted our preregistered model on the

367 basis of the insights described above. First, instead of specific trust and general

368 gratifications we now included general trust and specific gratifications (which were also

369 correlated slightly less strongly with one another). The adapted model fit our data

370 comparatively well, $\chi^2(508)$ = 1527.27, p < .001, cfi = .92, rmsea = .06, 90% CI [.06, .07],

371 srmr = .06.

372   In the adapted privacy calculus model, we found two additional significant effects.

373 For example, specific gratifications predicted self-disclosure online (β = .21, b = 0.17, 95%

374 CI [0.04, 0.31], z = 2.47, p = .013). Furthermore, in this model people who engaged in

375 more privacy deliberation did not disclose less information (β = -.13, b = -0.05, 95% CI

376 [-0.11, < 0.01], z = -1.85, p = .065). However, note that the effect was only marginally not

377 significant. Self-efficacy remained substantially correlated with self-disclosure (β = .28, b =

378 0.17, 95% CI [0.10, 0.24], z = 4.51, p < .001). We again found a negative correlation

379 between trust and self-disclosure (β = -.16, b = -0.13, 95% CI [-0.26, > -0.01], z = -2.00, p

380 = .045), which, as a sign of multicollinearity, suggests that also general trust and specific

381 gratifications should not be analyzed within the same model either.

382   Given that we observed several instances of multicollinearity, we also fitted a simple

383 privacy calculus model containing only privacy concerns and specific gratifications. The

384 simple model fit our data well, $\chi^2(202) = 734.29$, $p < .001$, cfi $= .94$, rmsea $= .07$, 90% CI

385 [.07, .08], srmr $= .06$. First, we found that people who experienced more privacy concerns

386 than others also disclosed less information ($\beta = -.13$, $b = -0.05$, 95% CI [-0.09, -0.02], $z =$

387 -3.09, $p = .002$). Second, people who reported more specific gratifications than others also

388 self-disclosed more information ($\beta = -.13$, $b = -0.05$, 95% CI [-0.09, -0.02], $z = -3.09$, $p =$

389 .002). Both effect sizes were above our predefined SESOI of $r = 0.10$, implying that the

390 effects were sufficiently large to qualify as support our the hypotheses. All effects labelled

391 as significant were below their individual Bonferroni-Holm corrected significance level. For

392 a visual overview of all results, see Figure 5.

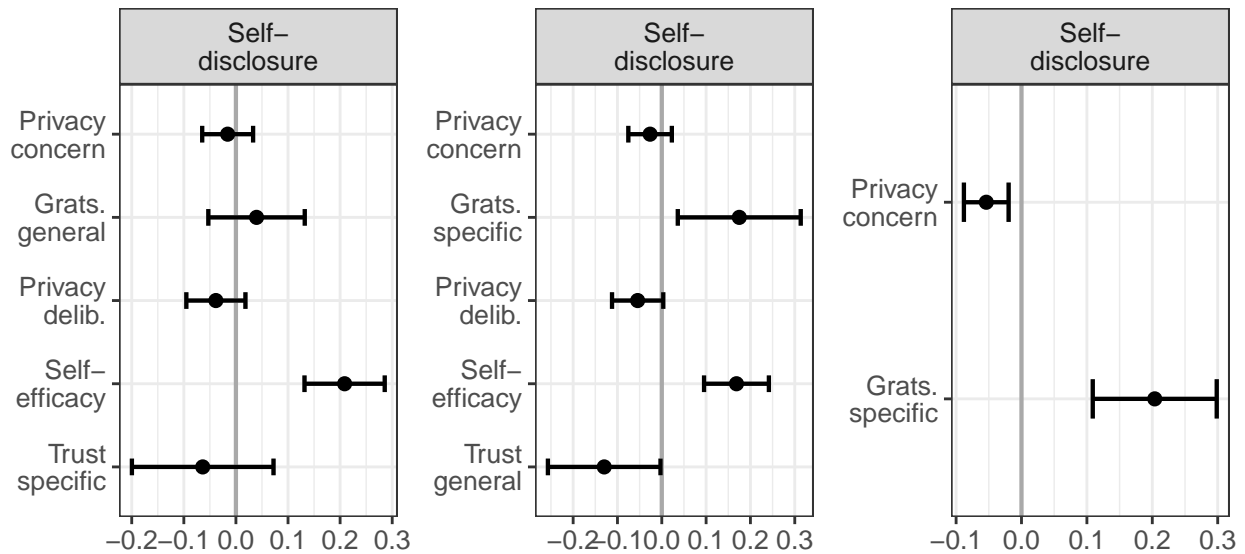*Figure 5*. Predictors of self-disclosure. Black lines indicate 90% CIs (for one-sided hypotheses), grey lines 95% CIs (for two-sided hypotheses).

393   When comparing the three models with one another, the simple privacy calculus

394 model was the most parsimonious one (BIC $= 33,786.44$, AIC $= 33,287.18$), followed by the

395 preregistered model (BIC $= 44,568.81$, AIC $= 43,988.99$) and the adapted model (BIC $=$

52,776.31, AIC = 51,970.17).

Popularity Cues

Preregistered analyses. Somewhat surprisingly, we found no effects of the popularity cues on the privacy calculus variables. For an illustration, see Figure 6, 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 with regard to the privacy calculus variables and the amount of self-disclosure.

Discussion

In this study, we analyzed theg e privacy calculus using actual observed behavior in a preregistered field experiment with data from a representative sample of the German population. We additionally sought to determine whether the privacy calculus is dependent on popularity cues such as like and dislike buttons. The data 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 turned out to be the strongest predictor of self-disclosure. However, this preregistered model exhibited significant problems with regard to multicollinearity, which is why we also computed a more basal privacy calculus model consisting of only privacy concerns and specific gratifications. In this model, both variables significantly and meaningfully predicted
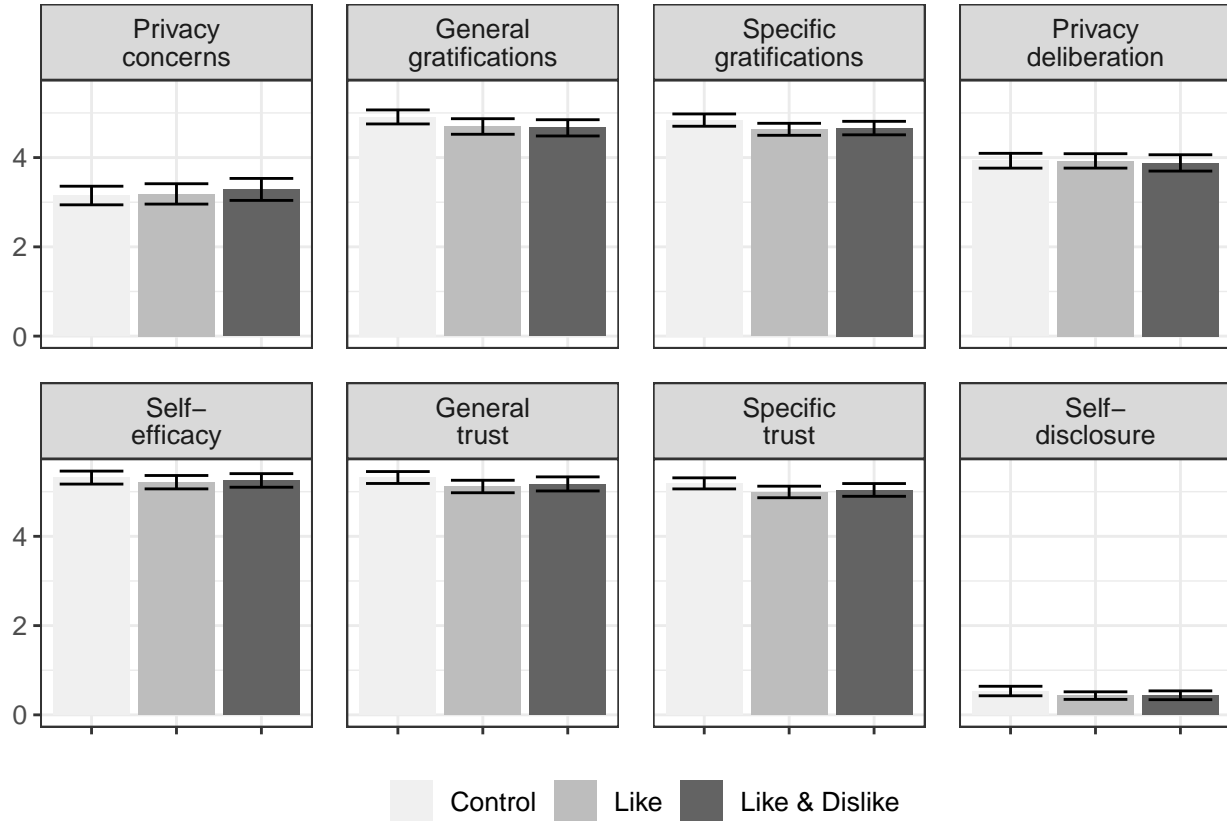
Figure 6. Overview of the variables for the three websites. Control: Website without buttons. Like: Website with like buttons. Like & Dislike: Website with like and dislike buttons.

self-disclosure. Taken together, the results add further support to the privacy calculus framework, suggesting that self-disclosure online is not erratic (as for example posited by the privacy paradox, for example) but—at least somewhat—considered.

Our 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 sould 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—evidenced by their strong correlation with

431 one another and their similar correlations with other variables. This either implies that

432 thinking about one's privacy increases one's concern or, conversely, that being concerned

433 about one's privacy leads one to think about one's options more actively. Future research

434 might tell.

435 The next major implication is that popularity cues do not seem to have an overly

436 strong influence on the privacy calculus and self-disclosure. Although some studies have

437 found that popularity cues substantially impact behavior (e.g., Muchnik et al., 2013), our

438 results suggest the opposite: Users still disclose the same amount of personal information

439 regardless of whether a website includes like or dislike buttons, potentially highlighting the

440 agency of users.

441 The results also have several more fine-grained implications. First, we question the

442 tendency to further increase the complexity of the privacy calculus model by adding

443 additional variables (e.g., Dienlin & Metzger, 2016). "Since all models are wrong the

444 scientist cannot obtain a"correct"it one by excessive elaboration. [. . .] Just as the ability

445 to devise simple but evocative models is the signature of the great scientist so

446 overelaboration and overparameterization is often the mark of mediocrity" (Box, 1976, p.

447 792). Although adding variables can increase the amount of explained variance, it might

448 also introduce spurious results due to multicollinearity—a problem that we think deserves

449 more attention in general. Specifically, we have come to believe that adding self-efficacy to

450 privacy calculus models is of limited value, for self-efficacy is mostly a proxy of behavior

451 and does not offer much epistemic insight. Instead, it might be more interesting to find out

452 *why* some people feel sufficiently efficacious to self-disclose whereas others do not.

453 Furthermore, we found a remarkably strong correlation between trust and expected

454 gratifications (i.e., $r = .77$), which at first glance seemed somewhat peculiar to us. On

455 closer inspection, however, we realized that the way trust is routinely operationalized in the

456 literature is very close to expected gratifications. To illustrate, one subdimension explicitly

457 measures *ability* via items such as "The comments of other users were useful". In fact, the

458 literature often operationalizes trust as a formative construct that directly results from

459 factors such as expected benefits (Söllner et al., 2016). In conclusion, our results suggest

460 that we should not confuse *causes* of trust with *measures* of trust, for this might introduce

461 problems of both homogeneity and/or multicollinearity.

Limitations

463   The results do not allow for causal interpretation on the within-person level. First, all

464 results are based on analyses of between-person variance. However, between-person

465 relations often do not translate well to within-person effects (e.g. Hamaker, Kuiper, &

466 Grasman, 2015). While some studies on privacy concerns online have begun to examine

467 both sources of variance (e.g., Dietvorst, Hiemstra, Hillegers, & Keijsers, 2017), finding

468 that intrapersonal changes in privacy concerns are indeed related to intrapersonal changes

469 in self-disclosure, similar analyses are still lacking for the privacy calculus. Second, the

470 self-reported measures were collected *after* the field phase in which the dependent variable

471 was measured. As a result, the coefficients might overestimate the actual relations, because

472 demand effects might have led participants to artificially align their theoretical answers

473 with their practical behavior to reduce dissonance. Nevertheless, we deliberately decided to

474 measure the self-reported variables afterward in order to not bias participants and not

475 prime our specific research interest. Third, experiments should only manipulate the

476 experimental variable while holding all others constant. In this study, we explicitly

477 manipulated the popularity cues. However, as the experiment was conducted in the field,

478 several other variables could not be held constant; for example, the content of

479 communication by other users, the unfolding communication dynamics, or the

480 characteristics of other users.

481   It is important to note that our not having found significant effects of like and dislike

482 buttons does not necessarily mean that like and dislike buttons do indeed have no effect on

483 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 the actual non-existence of effects or, instead, a poor operationalization of the research question. In this case, we were not able send participants notifications when their comments were liked/disliked, significantly decreasing 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.[3] It is worth noting that 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 increasingly accurate inferences about one's personality to be made.

Finally, there are several interesting research questions that one could address with the data. Most prominently, one could analyze the actual content of the posts to detect whether the three websites might have differed with regard to communication quality. In addition, one can make the case that privacy deliberation rather as a moderator—such that deliberating more actively about one's privacy strengthens the relation between privacy concerns or gratifications and self-disclosure. Upon publication, the data will be made publicly available and we invite researchers from all disciplines to investigate the aforementioned and other interesting research questions.

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

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[3] Somewhat fittingly, in the German language there is a saying: "He spoke a lot but didn't say a thing".

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. Popularity cues seem to play 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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