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The Effects of Positive Feelings and Arousal on Privacy Decision-Making

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THE EFFECTS OF POSITIVE FEELINGS AND AROUSAL ON PRIVACY DECISION-MAKING

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Abstract

The goal of this study is to contribute to the underexplored interplay of unrelated positive feelings and arousal and their effects on users' willingness to provide personal data. To this end, we conduct an online survey (n=368) based on a hypothetical social network sweepstake scenario in which personal data, such as a photo, must be disclosed for participation. We perform structural equation modeling based on an extended privacy calculus model. Drawing on the feelings-as-information theory, more positively valenced feelings, even when evoked by an unrelated stimulus, should lead to a higher willingness to disclose personal data and participate in the sweepstake. We examine how arousal influences this effect as well as users' willingness to disclose. We find three significant crossover interactions for unrelated positive feelings and arousal, i.e., for more positively valenced feelings under higher arousal levels users are more willing to disclose data which is in line with the feelings-as-information theory. Surprisingly, less positively valenced feelings under low arousal levels also lead to a higher willingness to disclose personal data. We explain these results by additionally drawing on the affect regulation theory, which assumes that individuals try to protect their feelings in positive affective states, and take actions in order to improve their feelings in less positive affective states. We interpret the arousal level as a "switch" that helps to determine which theory is suited best to predict the direction of the effect of unrelated positive feelings and thus, explain the observed crossover interactions: for high arousal levels, the feelings-as-information theory and for low arousal levels, the affect regulation theory fits best.

Keywords: Arousal, Emotions, Feelings, Personal Data Disclosure, Privacy Calculus.

1 Introduction

For every organization, it is important to know their users well to be able to personalize services and offer high value (Gartner, 2019). As a basis for successful value creation with personalized services it is necessary to acquire personal information: digital companies collect personal data, e.g., by analyzing user behavior on their websites (Weise, 2019) or by acquiring data more directly by organizing sweepstakes (Sendinblue, 2019), which can attract new users while also offering the possibility to learn more about them. It is especially important to know how users behave when disclosing personal data to be successful in data collection and personalization efforts. An often used theory to explain users' disclosure intention is the privacy calculus which assumes a weighing of benefits and privacy risks associated with the disclosure of personal data (Smith, Dinev and Xu, 2011). The privacy calculus is based on the theory of reasoned action, which assumes a purely "rational assessment" (Ajzen and Fishbein, 1980; Y. Li, 2012; Dinev, McConnell and Smith, 2015). This may be better described as a high-cognitive-effort decision-making process (Dinev et al., 2015).

However, to only consider high-cognitive-effort processing seems inadequate to explain disclosure decisions (Dinev et al., 2015). Thus, Dinev et al. (2015) call for more consideration of low-cognitive-effort processing in the disclosure making process. Likewise, many dual-process-theories suggest that both high-cognitive-effort processing as well as low-cognitive-effort processing play an important role in decision-making (Denes-Raj and Epstein, 1994; Slovic, Finucane, Peters and MacGregor, 2004; Kahneman, 2012; Evans and Stanovich, 2013). Some studies have already considered low-cognitive-effort processing, mostly with focus on emotional states that are directly related to the disclosure decision (e.g., Anderson and Agarwal, 2011; Wakefield, 2013; Kehr, Kowatsch, Wentzel and Fleisch, 2015; H. Li, Luo, Zhang and Xu, 2017).

We want to further contribute to this underexplored research field by focusing on the influence of unrelated feelings, i.e., feelings that were evoked by a decision-unrelated stimulus, as an instance of low-cognitive-effort processing. Previous studies showed that individuals oftentimes misattribute their feelings, which could make even unrelated feelings a factor that impacts privacy decisions (Schwarz and Clore, 1983; Antonetti and Valor, 2020). The *feelings-as-information theory* assumes that positive feelings lead to a more positive judgement even regarding objects or assessments that are not related to the feelings or its stimulus (Schwarz and Clore, 1983, 2003). According to this theory, positively valenced feelings, even when unrelated to the disclosure decision, could be the reason for distorted disclosure behavior whereby the individuals oftentimes tend to provide more personal data than intended (cf. Smith et al., 2011; Dinev et al., 2015). To better understand this issue, we focus on positively valenced unrelated feelings in this study. The focus of this study on feelings that are unrelated to the disclosure decision complements the privacy research on feelings that are related to the disclosure decision (e.g., Anderson and Agarwal, 2011; Wakefield, 2013; Li et al., 2017).

Another aspect we want to address in the context of online privacy and low-cognitive effort processing is the impact of arousal: in other research fields the impact of arousal on decision-making is already acknowledged, for example the effect of arousal on individuals' risk perception in daily life (Hogarth, Portell, Cuxart and Kolev, 2011). Previous research also indicates that higher arousal levels increase individuals' decision-making based on low-cognitive-effort heuristics (cf. Lambert et al., 2003; Ariely and Loewenstein, 2006; Ditto et al., 2006), e.g., drawing on positive feelings for decision-making. However, only few and rather recent studies in the privacy context start to consider arousal as an important factor that alters individuals' personal data disclosure decision-making (e.g., Coker and McGill, 2020). Therefore, we are interested in the effects of positively valenced unrelated feelings and arousal on users' data disclosure decision-making, which leads to the following research question:

How do positively valenced unrelated feelings and arousal levels impact individuals' willingness to disclose personal data?

In order to address this research question, we conducted an online survey (n=368), in which the participants were given a hypothetical scenario to disclose personal data to participate in a social network site's (SNS) sweepstake. The participants were split into two groups. In the treatment group participants recalled an autobiographical happy event before the sweepstake scenario in order to evoke positive feelings unrelated to the disclosure task (cf. Martin, 1990). To explore the main and interaction effects of unrelated positive feelings and arousal levels on users' willingness to disclose and participate in a SNS-sweepstake, we use an extended form of the privacy calculus for the structural equation model. We find that positively valenced feelings as well as arousal levels directly increase perceived benefits. We also find significant crossover interaction effects of unrelated positive feelings and arousal on the disclosure willingness as well as on its antecedents in form of perceived privacy risks, and perceived risk severity.

In sum, we contribute to a refined understanding of the interplay of positive unrelated feelings and arousal levels: in this study, arousal levels determine whether the effect of unrelated positive feelings increase or decrease users' disclosure willingness. This confirms the need for future research to consider both, feelings and arousal levels, as only taken together, a more precise prediction of users' behavior can be made. Furthermore, we inform practitioners about the possibility to increase users' disclosure willingness by increasing the arousal level and evoking positively valenced feelings with an unrelated stimulus. However, we also discuss possible countermeasures for users that allow them to make decisions without being biased towards overdisclosure by those evoked feelings. With these discussed countermeasures, our study serves as a thought-provoking impulse for legislators to also consider non-cognitive factors, like unrelated feelings or arousal levels, which additionally could be considered to prevent individuals from overdisclosure of personal data.

2 Theoretical Background and Hypotheses Development

2.1 Privacy Calculus and Privacy Concerns

The privacy calculus is the dominant theory to explain users' personal data disclosure behavior (Smith et al., 2011; Dinev et al., 2015). The privacy calculus draws on the *maximum utility theory*, which means that users strive for the option with the highest utility among two or more possible decisions (Y. Li, 2012). Therefore, users intend to disclose their data only when they perceive a higher utility for disclosure compared to no-disclosure. The calculated utility results from a weighing of perceived benefits (e.g., monetary rewards or social benefits like easier communication with friends) and perceived costs. Costs in the context of data disclosures are mainly reflected by the privacy risks (e.g., loss of personal data or getting spam-mails) associated with data disclosure (Awad and Krishnan, 2006; Bansal, Zahedi and Gefen, 2010; Y. Li, 2012).

For this weighing task of benefits and privacy risks, a high-cognitive-effort calculation is mostly assumed, which is a limitation of the privacy calculus (Dinev et al., 2015). This cognitive aspect can be exemplarily illustrated when looking at how traditional literature explains individuals' risk assessments: the perceived risk of experiencing an unfavorable outcome is calculated by individuals with their perceived probability of the uncertain outcome multiplied by the perceived severity of the respective outcome (Sieber and Lanzetta, 1964; Cunningham, 1967). Thus, the higher the probability and/or the severity in the mind of the users, the higher the perceived privacy risk (Keith, Thompson and Greer, 2012). Therefore, we consider in our base model not only users' perceived benefit and perceived privacy risk, but we also include perceived severity and probability as antecedent for perceived privacy risk.

Besides perceived privacy risk, users' privacy concerns also decrease their disclosure willingness (Y. Li, 2012; Dinev et al., 2015). However, previous studies found mixed results regarding privacy concerns. Some studies found a direct effect on disclosure willingness (e.g., H. Li et al., 2017), while other studies found only an indirect effect on disclosure willingness which was mediated by perceived

privacy risks (e.g., Keith et al., 2012; Kehr et al., 2015). We interpret privacy concerns as a rather general, non-situational construct and thus, as an antecedent to privacy risks. However, we additionally test the direct effect of privacy concerns on willingness to disclose and participate in the sweepstake. This leads to the base model displayed in Figure 1.

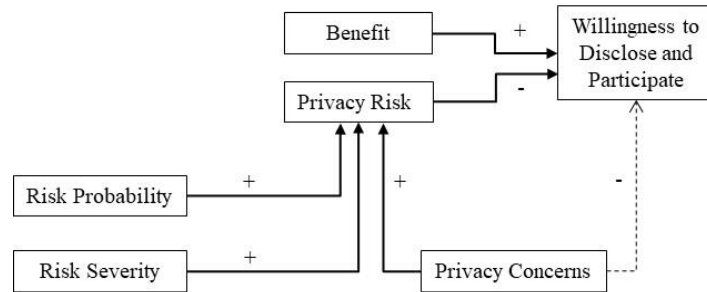


Figure 1. Structural equation base model

2.2 Low-Cognitive-Effort Processing

An attempt to understand users' data disclosure behavior in more detail is to not only consider their highly effortful cognitive utility assessments, but instead to also consider simpler assessments that only demand low cognitive effort (Dinev et al., 2015). Many researchers provide evidence for two processing systems (Epstein, 1994; Slovic et al., 2004; Kahneman, 2012; Evans and Stanovich, 2013). For example, Kahneman (2012) explains that there are two processing systems that both impact decision-making but behave completely differently: i) type one is intuitive, fast and automatic, requiring only low cognitive effort and ii) the second type is reasoning, slow and requires high cognitive effort like the above described privacy calculus or the risk assessment based on probability and severity displayed in our base-model.

But such a risk assessment, for instance, can also be done by the more intuitive processing system of type one which requires only low cognitive effort. Therefore, this system can depend on individuals' feelings, affective states or their intuitive reactions towards a certain situation (e.g., a data disclosure in form of a SNS-sweepstake participation) and its available cues (Loewenstein, Weber, Hsee and Welch, 2001; Slovic et al., 2004).

2.2.1 Feelings

There is a wide range of affective phenomena which also leads to some confusion or ambiguous use of certain terms, such as affect, mood, emotions and feelings (Rosenberg, 1998; Zhang, 2013). In this study, mood, feelings, and emotions are considered as a more specific manifestation of the umbrella term *affective state*. There is consensus that most affective states can be describe by their *valence*, i.e., the degree of pleasantness and unpleasantness, and their *arousal level*, i.e., their activation value (Russell, 2003; Zhang, 2013). A certain *mood* has oftentimes no specific stimulus and the affective state remains for a longer duration (Russell, 2003; Zhang, 2013). In contrast, we interpret emotion based on previous literature as an affective state induced by a certain stimulus. Thus, emotions are a reaction towards an object, or a certain behavior. Such evoked emotions have a shorter duration than a mood (Russell, 2003; Clore and Schnall, 2005; Scherer, 2005). We use the terms emotions and *feelings* as interchangeable synonyms of these short-lived feelings that are evoked by a certain stimulus (cf. Zhang, 2013).

The importance of feelings is discussed in Loewenstein et al.'s (2001) *risk as feelings theory*. This theory assumes that objectively relevant as well as non-relevant situational cues like the vividness or immediacy of the respective unfavorable outcome can impact individuals' feelings and their decision-making process.

Besides Loewenstein et al. (2001), other researchers confirm that low-cognitive-effort processes, e.g., in form of feelings, can influence decisions as well as the underlying cognitive evaluations (Schwarz and Clore, 1983; Petty and Cacioppo, 1986; Kahneman, 2012; Zhang, 2013). For example, positive feelings increase the decision intention itself (Wakefield, 2013). Positive feelings can also influence the cognitive evaluation process: positive emotions can decrease perceived privacy risk (Loewenstein et al., 2001; Chaudhuri, 2002; H. Li, Sarathy and Xu, 2011; Kehr et al., 2015; Bidler, 2020) and increase privacy protection beliefs or perceived benefit (H. Li et al., 2011; Kehr et al., 2015; Bidler, 2020).

2.2.2 Unrelated Feelings

Previous research has shown that feelings are often misattributed by individuals but nevertheless serve as robust and important determinants of assessments (Schwarz and Clore, 1983; Higgins, 1998; Dunn and Schweitzer, 2005). In this regard, the *feelings-as-information theory*, also known as the *mood-as-information theory*, was developed (Schwarz and Clore, 1983, 2003). This theory assumes that individuals use their feelings as source of information for the assessment of the current situation. This means, individuals assess an object more positively when they have more positively valenced feelings (Schwarz and Clore, 1983, 2003). In line with the feelings-as-information theory, more recent research, for example by Antonetti and Valor (2020), suggests that feelings toward a certain target A can spill over to another target B. Thus, feelings can influence judgements and decision-making processes despite being evoked by decision unrelated stimuli (cf. Schwarz and Clore, 2003; Dunn and Schweitzer, 2005; Harlé and Sanfey, 2007). Based on the feelings-as-information theory, we hypothesize that feelings evoked by stimuli unrelated to a certain personal data disclosure can influence users' willingness to disclose.

For example, individuals who obtained a product as a gift from a smiling person they liked, had a more positive attitude towards the product than persons who obtained the product from a person they did not like (Howard and Gengler, 2001). Similar results were obtained by Bidler et al. (2020) in the privacy context: positive affective reactions towards data disclosures inflate unrelated benefits and decrease unrelated risks. Thus, we argue that the effects of positively valenced feelings unrelated to the decision are similar to the effects of decision related positive feelings (cf. chapter 2.2.1). Therefore, we hypothesize that positively valenced unrelated feelings increase disclosure willingness as well as perceived benefit and decrease perceived privacy risk regarding a data disclosure in form of a SNS sweepstake participation:

H1a: Positively valenced unrelated feelings increase users' willingness to disclose.

H2a: Positively valenced unrelated feelings increase users' perceived benefit.

H3a: Positively valenced unrelated feelings decrease users' perceived privacy risk.

We expect that feelings can equally influence the antecedents of perceived privacy risk. Slovic et al. (2004) discuss that feelings impact the perception of probabilities, which is exemplarily illustrated in the studies by Slovic, Monahan and MacGregor (2000) and Yamagishi (1997). They show that giving information about the probability of a certain risk in form of the number of affected individuals compared to a percentual share. The more affect-laden number of affected individuals leads to a higher risk perception. Equally, warnings in form of affect-laden scenarios are more influential than warnings in form of relative frequencies (Hendrickx, Vlek and Oppewal, 1989). Also, individuals provided with narrative information (rather affect-laden) can better predict outcomes than individuals provided with bars and data tables (Sanfey and Hastie, 1998). More evidence for the effects of the low-cognitive-effort system can be found in the study of Hogarth, Portell and Cuxart (2007): happy feelings reduce perceived risk probability and severity. Thus, we hypothesize analogously to the aforementioned hypotheses, that even unrelated positive feelings can decrease perceived risk severity and probability (cf. Howard and Gengler, 2001; Bidler, 2020):

H4a: Positively valenced unrelated feelings decrease users' perceived privacy risk probability.

H5a: Positively valenced unrelated feelings decrease users' perceived privacy risk severity.

2.2.3 Arousal

In order to understand individuals' reliance on the low-cognitive-effort system, arousal could help as this seems to alter individuals' assessments (Lambert et al., 2003; Ditto et al., 2006; Coker and McGill, 2020). Arousal is mostly described as an intensity dimension belonging to an emotional response (Deng and Poole, 2010). In line with this, we interpret high levels of arousal as an activation state of the organism, e.g., wide-awake (Deng and Poole, 2010). One mechanism that explains stronger reliance on low-cognitive-effort processing could lie in an increased arousal level. An increased arousal level could make low-cognitive-effort processing, respectively affective assessments, for decision-making more salient than analytical high-cognitive-effort processing (Svenson and Maule, 1993; Finucane, Alhakami, Slovic and Johnson, 2000; Lambert et al., 2003; Coker and McGill, 2020; Kim et al., 2020). For example, the reliance on stereotypical thinking is increased under high arousal levels (Lambert et al., 2003). Also, sexual arousal in males lead to an increased perception of womens' attractiveness, increased willingness to engage in morally questionable behavior or willingness to engage in unsafe sex (Ariely and Loewenstein, 2006). Similarly, individuals are more willing to have unsafe sex when they see a video instead of a description, i.e., when they were stronger aroused sexually (Ditto et al., 2006). Another study shows that individuals are more willing to risk their time to win cookies when they can see and smell them, i.e., when they are more strongly aroused, compared to individuals who cannot see and smell the cookies (Ditto et al., 2006). In the privacy context, an increased disclosure behavior is associated with higher levels of arousal (Coker and McGill, 2020). Thus, we expect that higher arousal reinforces the effects of positively valenced feelings and hypothesize accordingly (see also Figure 2):

H1b: Positively valenced unrelated feelings increase users' disclosure willingness stronger under high arousal levels than under low arousal levels.

H2b: Positively valenced unrelated feelings increase users' perceived benefit stronger under high arousal levels than under low arousal levels.

H3b: Positively valenced unrelated feelings decrease users' perceived privacy risk stronger under high arousal levels than under low arousal levels.

H4b: Positively valenced unrelated feelings decrease users' perceived privacy risk probability stronger under high arousal levels than under low arousal levels.

H5b: Positively valenced unrelated feelings decrease users' perceived privacy risk severity stronger under high arousal levels than under low arousal levels.

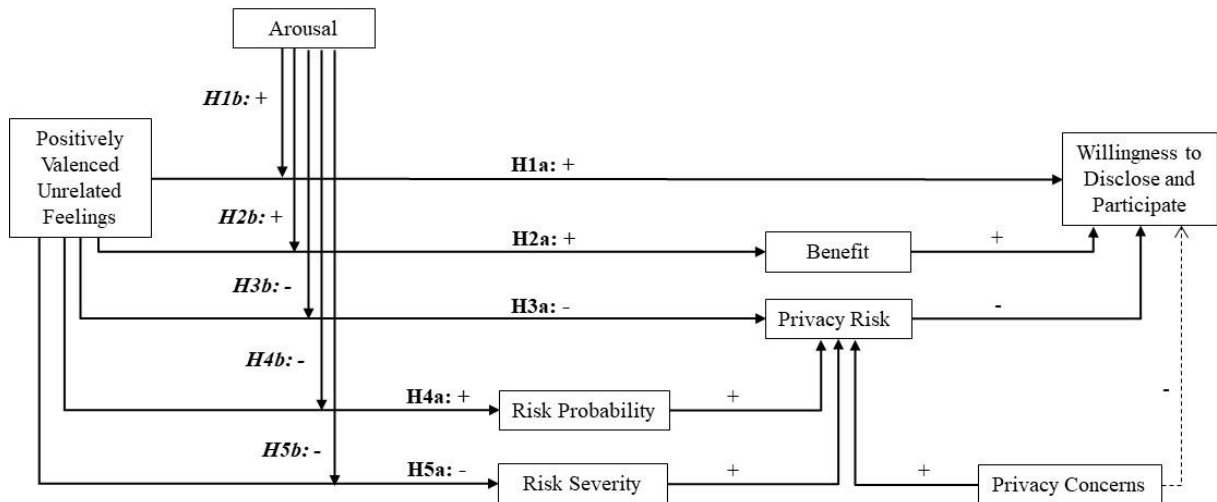


Figure 2. Structural equation model with an overview of the hypotheses. The direct effects of arousal on benefit, privacy risk, risk probability and risk severity are also tested, as it is necessary in order to test the interaction effects. For simplicity, these direct effects of arousal are not displayed in the model despite being tested.

3 Sample and Setup

Our survey was structured as follows: first, participants submitted demographic information, i.e., their age, sex, but also whether they have an Instagram account and are interested in the 1. or 2. Fussball-Bundesliga. Only when they were above 18 years old and had an Instagram account and were also interested in the 1. or 2. Bundesliga (due to the sweepstake context), they were able to continue the survey. A pre-test was conducted to verify the understandability of the survey. Afterwards, the survey data was collected from October until early November 2020 in cooperation with a panel provider in Germany.

We split the participants in two groups: in the treatment group (“happy” group) we let the participants recall a positive experience that made them feel happy. They were encouraged to imagine their experience as vividly as possible and to focus on the feelings that were evoked in this situation. They were asked to narrate their experience with up to 150 words. This method is known as autobiographical recall and is used to evoke positive affective states (Martin, 1990). It is thought to be a more effective manipulation of feelings than music and guided imagery combined and additionally, it is suited to be applied in an online survey (Westermann, Spies, Stahl and Hesse, 1996; Jallais and Gilet, 2010). We also verified that these positively valenced feelings were evoked by situations which were not related to the context of this study by reading their experience description before analysing the data. After the feeling manipulation, we measured participants’ positively valenced unrelated feelings (PVUF) (Klapwijk and Van Lange, 2009) and arousal levels (AR) with a common semantical measurement instrument (Deng and Poole, 2010). The control group was not encouraged to re-experience a positive situation of their life. Instead, participants’ positive feelings and their arousal level was measured instantly, i.e., without any induction.

After these measurements, both groups were shown the exact same hypothetical scenario: participants had to imagine that the panel provider recommends an Instagram sweepstake, in which they can win one of two soccer jerseys of their favorite 1. or 2. Fussball-Bundesliga club. Additionally, the respective Instagram post was shown to the participants. The sweepstake is from a goalkeeper young talent training organization. It is a common Instagram sweepstake in which the Instagram account has to be followed and the post has to be liked as well as commented in order to participate. Additionally, for participation, one has to share a photo of oneself as a fan of one’s favorite club with the organization’s Instagram account. To make the hypothetical scenario as realistic as possible, we

displayed an image of the organization's official Instagram account. As an optional information source, participants could access even more information about the company, (i.e., information about the founder and employees as well as the company's aim).

After displaying the scenario to the participants, we measured their willingness to disclose and participate in the sweepstake (WDP), the perceived benefits (BENE) and privacy risks (RISK) associated with the participation, the perceived risks probability (PROB) and severity (SEV), and additionally their general privacy concerns (PC). For detailed measurement instrument information see Table 2 in the Appendix.

We ensured that the participants carefully read the questions and items of the survey. We obtained 368 valid observations that met the described criteria ("happy" group: $n=177$; control group: $n=191$; with an average age of 39 and with 50% females in total; for details on the participants' distribution see Table 3 in the Appendix).

4 Results

We verify via Fisher's permutation test that there are no differences between the two groups regarding sex ($\Delta=.01$, $p=.833$), age ($\Delta=1.28$, $p=.385$), general privacy concerns ($\Delta=.07$, $p=.617$), and arousal levels ($\Delta=.09$, $p=.547$). With the same method, we confirm the autobiographical manipulation in the happy group to be successful, i.e., that participants in the happy group have more positively valenced unrelated feelings ($\Delta=.34$, $p=.007$). We analyze our data with SmartPLS (version 3.3.2), which applies the partial least squares method (Wold, 1966; Joe F. Hair, Ringle and Sarstedt, 2011). Partial least squares structural equation modeling is particularly suited for predictive as well as exploratory research as done in this study. Furthermore, there are no distributional requirements for this method (Joe F. Hair et al., 2011). We use this method to test the measurement model as well as the hypothesized structural model (cf. R. P. Bagozzi and Yi, 1989; Gefen, Straub and Boudreau, 2000; J. F. Hair, Hult, Ringle and Sarstedt, 2016).

4.1 Measurement Model Assessment

We test for i) internal consistency reliability, ii) convergent validity, and iii) discriminant validity (J. F. Hair, Sarstedt, Ringle and Gudergan, 2017).

i) Cronbach's α as well as composite reliability for all constructs are above the lower threshold of 0.7 (Richard P. Bagozzi and Yi, 2012), thus internal consistency reliability is achieved.

ii) In order to verify convergent validity, we assess the item loadings as well as the average variance extracted (AVE). The outer loadings of the items on their respective constructs should exceed 0.7 (Richard P. Bagozzi, Yi and Phillips, 1991; Joe F. Hair et al., 2011) but at least be above 0.4 (Henseler, Ringle and Sarstedt, 2015). All items' outer loadings are above 0.7, except for two items in the privacy concern measurement instrument. These two items have outer loadings above 0.6. This is still acceptable, as those items capture different aspects of privacy concerns and those items were taken from a well-established measurement instrument. The AVE for the constructs should exceed the threshold of 0.5 to confirm convergent validity (Joe F. Hair et al., 2011), which applies to all constructs.

iii) We confirm discriminant validity, by verifying that the following three criteria are met: all item loadings are greater than the respective cross-loadings on other constructs (Richard P. Bagozzi and Yi, 2012), the Fornell-Larcker criterion is met (Fornell and Larcker, 1981), and the constructs' heterotrait-monotrait ratios (HTMT) are even below the conservative threshold of 0.85 (Henseler et al., 2015).

4.2 Structural Model Assessment

Next, we assess the structural model and the hypothesized relationships. To verify that no collinearity issues are present between the exogenous latent variables, the variance inflation factors (VIFs) must be below the threshold of 5 for each construct (Thatcher and Perrewé, 2002). All VIF values are even below 1.43 (cf. Appendix Table 6 for details).

We perform a bootstrap procedure with 5,000 bootstrap samples to evaluate the significance of the path coefficients (two-sided).

In our estimated structural model as displayed in Figure 3, all path coefficients in our base-model have the expected directions and are highly significant. Regarding the direct effect of general privacy concerns on willingness to participate, we observe no direct significant effect. Instead, we only find an indirect significant effect of privacy concerns on the participation willingness, which is in line with our assumption, mediated by perceived privacy risks. Details of the path coefficient results are provided in Table 4 in the Appendix.

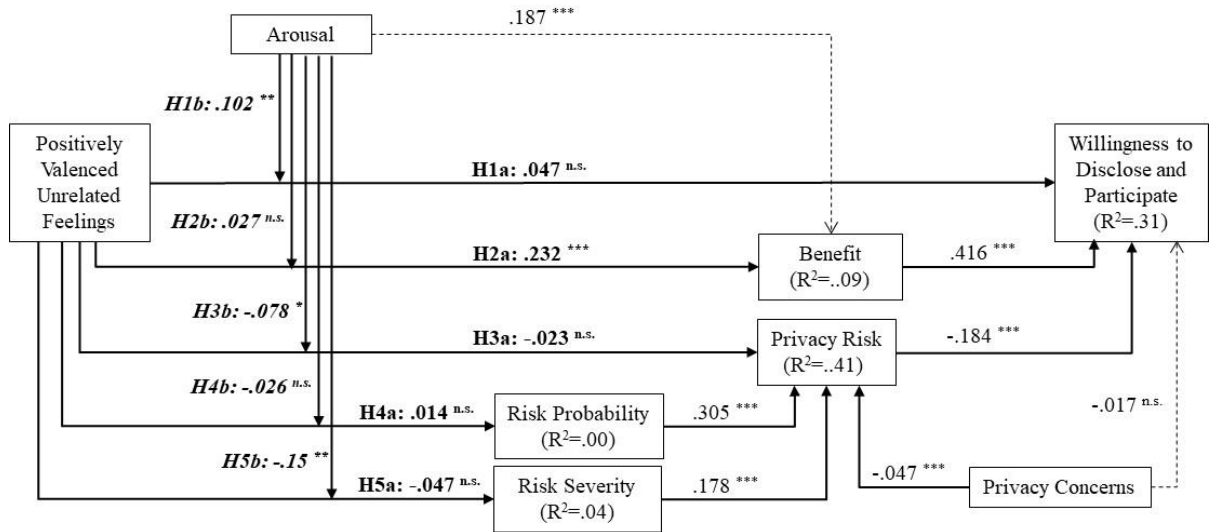


Figure 3. SEM results. Unhypothesized relationships are in dotted lines. Significance levels: $n.s.$ $p > .05$; $*$ $p \leq .05$; $**$ $p \leq .01$; $***$ $p \leq .001$. The direct effects of arousal on privacy risk, risk probability and risk severity are also tested and are not-significant (see Table 4 in the Appendix). For simplicity, the non-significant direct effects of arousal are not displayed in this model despite being tested.

In Table 1, we additionally provide the effect sizes (f^2). All effects in our base model are above the lower threshold of 0.02 (Cohen, 1988). Thus, our further analyses focus only on the hypothesized effects. We reject hypothesis 1a, as more positively valenced unrelated feelings do not significantly increase users' willingness to participate ($r = .047$, $p = .344$, $f^2 = .003$). However, we find a significant interaction effect of arousal and positive feelings ($r = .102$, $p = .007$, $f^2 = .018$). The size of the interaction effect remains slightly below Cohen's threshold of 0.02 for direct effects (Cohen, 1988; J. F. Hair et al., 2016). However, all observed interaction effect sizes in this study are still above the average interaction effect size published in psychological journals (Aguinis, Beaty, Boik and Pierce, 2005; Kenny, 2015). Regarding our interaction effects, the observed effect sizes should be rather interpreted as medium to large (cf. Kenny, 2015). Therefore, we accept H1b. When examining the slope (Figure 4, left), we observe that when users experience more positively valenced unrelated feelings, their willingness to participate increases under high arousal, but decreases under low arousal levels. Furthermore, in Figure 4 (left) we can observe that this is a crossover interaction effect (Loftus, 1978). This means that under less positively valenced feelings, the effect of arousal is inversed: with

less positively valenced feelings, higher arousal leads to a reduced willingness to participate while under low arousal levels, this results in an increase for users' willingness to participate.

Table 1. Resulting effect sizes. Bold: $f^2 > .02$; italic: $.02 > f^2 > .01$

IV	DVs					
	AR	PROB	SEV	RISK	BENE	WDP
PVUF		.000	.002	.001	.059	.003
AR		.000	.001	.000	.037	.009
PVUFxAR		.001	.029	.012	.001	.018
PROB				.145		
SEV				.039		
PC				.151		
RISK						.035
BENE						.221

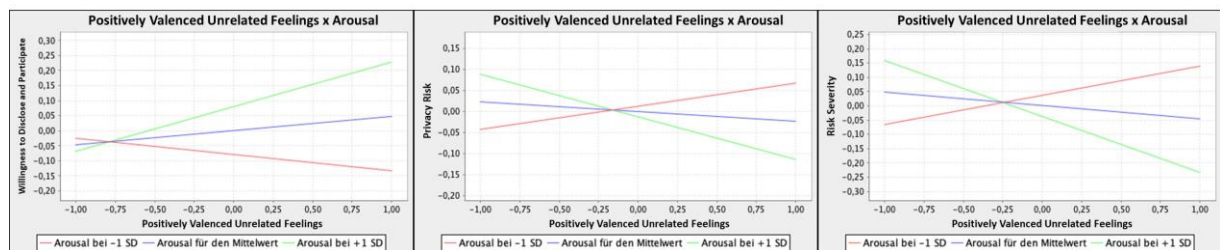


Figure 4. Slope analysis of interaction effects. Left: H1b; middle: H3b; right H5b.

More positively valenced unrelated feelings increase users' perceived benefit significantly ($r = .232$, $p < .001$, $f^2 = .059$), thus we accept H2a. We find no significant interaction effect of positively valenced feelings and arousal ($r = .027$, $p = .575$, $f^2 = .001$). Thus, we reject H2b. However, instead of an interaction effect of arousal, we observe a direct increasing effect of arousal on users' perceived benefits ($r = .187$, $p < .001$, $f^2 = .037$).

We reject H3a as more positive feelings do not significantly decrease users' perceived privacy risk ($r = -.023$, $p = .619$, $f^2 = .001$). Regarding H3b, we find a significant interaction effect of arousal and positive feelings, which leads to a reduced privacy risk perception under more positively valenced feelings and high arousal levels ($r = -.078$, $p = .045$, $f^2 = .012$). Again, the interaction effect size is slightly below Cohens threshold of .02, but still higher than the average reported interaction effect sizes in social sciences (Cohen, 1988; Aguinis et al., 2005; Kenny, 2015). Therefore, we also accept H3b. Slope analysis (Figure 4, middle) shows that this is a crossover interaction effect (Loftus, 1978): more positively valenced feelings together with high arousal levels lead to a reduced privacy risk perception while under lower arousal levels this results in higher privacy risk perceptions. For less positively valenced feelings, the influence of arousal is inversed: under high arousal levels, users' privacy risk perception is increased while under low arousal levels, users perceive a decreased privacy risk.

We reject H4a as more positively valenced unrelated feelings do not decrease users' perceived risk probability ($r = .014$, $p = .809$, $f^2 < .001$). In this regard, positive feelings and arousal have no significant interaction effect ($r = -.026$, $p = .677$, $f^2 = .001$), thus we also reject H4b.

We also could not observe an effect of unrelated positive feelings on users' perceived risk severity ($r = -.047$, $p = .405$, $f^2 = .002$). Therefore, we reject H5a. However, arousal and unrelated positive feelings have a significant interaction effect on perceived risk severity ($r = -.150$, $p = .004$, $f^2 = .029$). When analyzing the slope (Figure 4, right), we observe again a crossover interaction effect (Loftus, 1978): more positively valenced feelings together with high arousal levels lead to a reduced risk severity perception while under low arousal levels this results in higher perceived risk severity. For

less positively valenced feelings the influence of arousal is inverted: under high arousal levels, an increase in perceived risk severity is observable while under low arousal levels, this results in a decreased risk severity perception.

5 Discussion

The results confirm our base model. We also verify that general privacy concerns do impact a specific disclosure decision only indirectly via perceived privacy risk. Regarding our main effect hypotheses, only the direct effect of positive feelings on perceived benefit (H2a) is significant. The direct effects of positive feelings on willingness to disclose and participate (H1a), on perceived privacy risk (H3a), on perceived privacy risk probability (H4a), and on perceived privacy risk severity (H5a) are not significant. However, the significant crossover interaction effects of positively valenced feelings and arousal (cf. Figure 4 and 5) on disclosure willingness (H1b), perceived privacy risk (H3b), and perceived risk severity (H5b) explain the non-significance of their respective direct effects (Loftus, 1978; Williams, 2015). These crossover interaction effects of positively valenced unrelated feelings and arousal are as follows: *under high arousal levels*, more positively valenced feelings lead to a decrease in users' perceived risk severity as well as perceived privacy risk, and to an increase in users' disclosure willingness. In contrast, *under low arousal levels*, more positively valenced feelings have the opposite effect, i.e., they lead to an increase in perceived risk severity and perceived privacy risk and lead to a decrease in disclosure willingness. However, for the observed crossover interaction effect on disclosure willingness, the increase in users' willingness to disclose under low arousal levels with less positively valenced feelings is weaker compared to the increase in users' willingness to disclose under high arousal levels with more positively valenced feelings.

The direct effects of arousal and positive feelings (H4a) as well as their interaction effect on perceived risk probability are not significant. Thus, perceived risk probability is the only tested construct on which unrelated positive feelings and arousal levels had no significant impact at all.

The remaining insignificant interaction effect is in H2b, which is the interaction effect on perceived benefit. The effects on perceived benefit are somehow exceptional, as the only significant direct effect of positively valenced feelings is on perceived benefit (H2a). Furthermore, in this case we observe the only significant direct effect of arousal, which increases perceived benefit. It seems that positive feelings and arousal are differently related to the benefit side of the privacy calculus compared to the privacy risk side. This could be related to the fact that when individuals apply simpler heuristics they generally tend to focus on the benefit side (Ditto et al., 2006). Also previous research has shown that higher arousal increases individuals' prize valuation respectively individuals bidding pricing in online auctions, which is explained with "auction fever" (cf. Adam et al., 2015). Taken together, these previous studies could help to explain why we find significant direct effects instead of an interaction effect in this regard. Nevertheless, to understand the reasons for the different impact of unrelated positive feelings and arousal on perceived benefits compared to the risk side of the privacy calculus, further research is necessary.

In sum, our results show that even unrelated positive feelings and the associated arousal levels can impact users' disclosure and participation willingness as well as its antecedents. Thus, it is indeed important to consider both constructs, positive feelings as well as arousal levels, and their interaction effects.

However, the most interesting observation in our study is that all significant interaction effects are crossover interactions (H1b, H3b, H5b), i.e., the arousal level serves as a "switch" for the effect: the effect sign is inverted when we compare the effect of unrelated positive feelings for users under high versus low arousal levels. A possible explanation for this observation could be that at different levels of arousal, different and sometimes contradictory theories fit best:

The highly aroused users behave as we expected: in line with the feelings-as-information theory (cf. Schwarz and Clore, 1983, 2003) positive feelings serve as informational input respectively as a basis for users' decision-making. As we assumed, users base their decision more strongly on these emotional information when highly aroused, which is in line with findings that higher arousal support simpler heuristics (Kim et al., 2020). In this case, individuals' positive feelings under high arousal increase more strongly their willingness to disclose and participate in the sweepstake (or reduce their risk perception more strongly) than when the individuals are not aroused. Equally, individuals with less positively valenced feelings under high arousal have a decreased willingness (higher risk perception) compared to individuals with low arousal levels.

However, this would only explain why the participation willingness is higher (or lower regarding risk perceptions) for users with high arousal levels. It does not explain why users' participation willingness (risk perception) increases (decreases) despite less positively valenced feelings under lower arousal levels.

This observation could be best explained by adopting an additional perspective: the *mood-maintenance theory* (Isen, 2000) assumes that positive feelings promote behavior that protects the current positive emotional state. The more developed *affect regulation theory* goes one step further and assumes that individuals in a positive affective state try to protect these positive feelings while individuals in a bad affective state take actions to improve their feelings (Andrade, 2005). Therefore, one explanation could be that unrelated positive feelings are seen under low arousal levels with less positively valenced feelings (more positively valenced feelings) as a good that could be won (lost) when disclosing personal data, e.g., in a sweepstake. For example, the latent possibility that personal data submitted during such a sweepstake participation could be misused could make users (under highly positively valenced feelings and low arousal levels) to anticipate that their positive feelings will vanish as this latent risk is in the back of their minds. In turn, this increases their risk perception and decreases their disclosure willingness. Vice versa, users with less positively valenced feelings under low arousal could expect that their feelings will become more positive when they get the benefit, i.e., win the prize of the sweepstake, and thus are rather willing to disclose. This perspective could also partially explain some previous observations that indicate that under low arousal states individuals ignore their positive feelings, or that these positive feelings do not lead to more optimistic assessments (Svenson and Maule, 1993; Ditto et al., 2006; Kim et al., 2020). It must be noted again, although this theory adequately explains and predicts users' disclosure behavior under low arousal levels, exactly the opposite disclosure behavior is observed for the high arousal level. For high arousal levels, only the feelings-as-information theory correctly explains and predicts users' disclosure behavior.

Therefore, it does seem as if users' arousal level serves as a switch that determines which of the theories explains and predicts users' disclosure behavior best:

i) *Low Arousal Level*. The affect regulation theory (Andrade, 2005) seems to fit best under low arousal levels as individuals with more positively valenced feelings want to keep their good "positive feelings" and have a lower motivation to engage in risky behavior. In contrast, users with currently less positively valenced feelings want to improve their feelings and thus are rather willing to disclose personal data respectively are more privacy risk prone. Thus, with this view we can explain that individuals with more positively valenced feelings under low arousal levels should assess the privacy risk as higher and they should be less willing to disclose their personal data compared to others and vice versa for users with less positively valenced feelings. This is exactly what we observed in our data for the interaction effect of more positively valenced unrelated feelings under low arousal levels for users' perceived privacy risk (H3b), perceived risk severity (H5b), and for their willingness to participate (H1b). However, for users under high arousal levels the affect regulation theory does not explain or predict users' disclosure behavior correctly.

ii) *High Arousal Level*. Whereas the feelings-as-information theory (Schwarz and Clore, 1983, 2003) fits best to explain and predict the disclosure behavior for highly aroused users. According to this

theory, users should perceive less privacy risk and be more willing to disclose their data with more positively valenced feelings since these are used as informational input that promotes optimistic assessments. This is exactly what we initially hypothesized and also observed for users under high arousal levels.

5.1 Limitations

Our results have to be viewed in light of their limitations: in our survey, only individuals who had an Instagram account and were interested in soccer were allowed to participate in the survey. Thus, our sample may not reflect the population as these participants could have, for instance, a generally higher willingness to share their data. Another aforementioned aspect are the rather small effect sizes which are above or only slightly below the 0.02 threshold of Cohen (1988). This was expected due to the nature of interaction effects, for instance, the median of published interaction effect sizes in psychological journals is $f^2 = .002$ ($f^2_{\text{mean}} = .009$; Aguinis et al., 2005; Kenny, 2015). All our interaction effect sizes are above .009. Thus, our interaction effect sizes should be interpreted as medium to large effect sizes (Aguinis et al., 2005; Kenny, 2015).

We only measured users' willingness to participate and not real behavior, which is not always in accordance with their stated intentions (cf. Norberg, Horne and Horne, 2007). Manipulating and actually measuring feelings as well as arousal levels in a real-life social network sweepstake setting would be the best option regarding external validity. However, it is hard to evoke only specific feelings in a real world setting as there are many confounding influences. Moreover, the measurement in a real-life setting is difficult on its own, but especially in times of the Covid-19 pandemic. Therefore, to measure only intentions or willingness to disclose is common practice in the privacy field as these are important and valid predictors for actual behavior (cf. Ajzen and Fishbein, 1980; Smith et al., 2011; Kehr et al., 2015; Gerber, Gerber and Volkamer, 2018; Al-Natour, Cavusoglu, Benbasat and Aleem, 2020).

Also, we did not invoke different levels of arousal in the participants. Instead, we only measured the arousal levels, which are similar for both groups. We argue that the sole measurement is sufficient for our study as the participants in the control group clearly can have different arousal levels depending on the situation, or the time of the survey participation. For example, participants in the "happy" group can recall different events in their life. For example, the recalled positive experience could either be a thrilling bungee jump experience or a relaxing sauna visit. Both would lead to more positively valenced feelings but different arousal levels. Thus, we argue that our study design seems to be sufficient as a basis for more detailed research on this topic. Nevertheless, we suggest a targeted manipulation of arousal levels in future studies so that the arousal levels differ between groups. Such a study design could be helpful to examine the effects of arousal in more detail.

5.2 Implications and Future Research

Our study offers several important contributions for theory:

Firstly, we contribute in a theoretical way to the scarce privacy literature that examines effects of unrelated feelings. We argue that unrelated feelings are especially important in the digital context, for example through unrelated stimuli in form of music, pictures, or social network posts and news that are just one click away to evoke certain feelings (Harlé and Sanfey, 2007; Hill, Rand, Nowak and Christakis, 2010; Thelwall, 2010; Kramer, Guillory and Hancock, 2014) and in turn impact personal data disclosure decision-making. This makes it essential to explore effects of unrelated feelings in more detail.

Therefore, this study helps to build a basic understanding of their effects. We showed that positively valenced unrelated feelings as well as arousal levels directly increase users' benefit perception without having a significant interaction effect. In contrast, we found that there is no direct effect of more

positively valenced feelings and arousal levels on perceived privacy risk, risk severity, risk probability, and on disclosure willingness. However, we showed that there are significant crossover interaction effects of positively valenced unrelated feelings and arousal levels on perceived risk severity and the total perceived risk and disclosure willingness but not the perceived risk probability. Future studies are necessary to understand in detail why and how arousal and positively valenced feelings affect benefit perception differently than risk perception.

Another contribution regarding the characteristics of the significant interaction effects is that they are crossover interaction effects. This means that more positively valenced feelings increase disclosure willingness and decrease privacy risk perception only in combination with high arousal levels, while under low arousal levels this results in the opposite effect. With this, it seems we discovered a new phenomenon in privacy decision-making, that is eventually only true for positive feelings evoked by decision unrelated stimuli but not for feelings that are evoked by decision related stimuli: to the best of our knowledge, all studies find clear evidence that decision related positive emotions only increase disclosure willingness and decrease perceived privacy risk (Anderson and Agarwal, 2011; H. Li et al., 2011; Wakefield, 2013). However, it is still possible that in these studies most participants were highly aroused, leading to a disclosure willingness increasing instead of decreasing effect for more positively valenced feelings. This would be in perfect accordance with our results, but we assume that not all participants were highly aroused in these studies. Instead, we could imagine that the inversion of the effect for positively valenced feelings under low arousal compared to high arousal levels will only happen for positive feelings that are evoked by decision unrelated stimuli. To address this issue, future studies should consider users' arousal levels in their studies to verify under which circumstances these crossover interaction effects happen. Additionally, privacy studies should also distinguish between feelings that are evoked by stimuli related and unrelated to disclosure decisions.

We also provide a first explanation for the observed crossover interaction effects. To do so, we combine perspectives of the feelings-as-information theory (Schwarz and Clore, 2003, 2003) with perspectives of the affect regulation theory (Andrade, 2005) by using users' arousal levels as a switch to decide which theory explains and predicts users' decision-making best. However, future studies should verify if our assumed explanation for the effect inversion can be used for prediction, i.e., that the affect regulation theory (Andrade, 2005) is appropriate for low arousal conditions while the feelings-as-information theory (Schwarz and Clore, 2003, 2003) is appropriate for high arousal conditions.

This study bears two important contributions for practice as well:

First, organizations that rely on personal data can increase potential users' data disclosure willingness when the organizations evoke positive feelings and high arousal levels right before the disclosure decision, even if the stimulus is unrelated to the disclosure decision. For example, this could be achieved by playing positive and arousing music, displaying a certain positive and arousing picture or simply by providing an exciting positive story (Westermann et al., 1996; Jallais and Gilet, 2010; Kramer et al., 2014; Kim et al., 2020). Similarly, it also could help to choose the right disclosure ad position and the right timing. Especially new in our study compared to previous research is, that we show that it is not necessarily sufficient to increase users' disclosure willingness by only evoking positive feelings. To evoke more positively valenced feelings and high levels of arousal at the same time seems to be the most effective way to increase users' disclosure and participation willingness. Under low arousal levels at worst more positively valenced feelings could lead to a decreased disclosure willingness.

This knowledge could be misused by organizations as users may make unwanted decisions when they are confronted with extremely feelings evoking stimuli. Therefore, we want to point out that there is a potential countermeasure for users to protect themselves from such distorted decision-making: individuals should think about their own feelings and find out the reason respectively the stimulus which evoked those feelings and realize that this stimulus is not associated with the decision. Studies in different contexts showed that this helped individuals who were confronted with positive feelings

inducing stimuli, to make decisions that resembles decision-making of individuals in the control group (cf. Schwarz and Clore, 1983; Ciarrochi, Caputi and Mayer, 2003). Furthermore, based on our results, individuals with very positively valenced feelings should try to calm down when they are very excited before making disclosure decisions in order to prevent overdisclosure of personal data. Nevertheless, future studies should examine how effective these countermeasures are in the online privacy context.

Second, this study could help policymakers as well. The meaningful interactions of positively valenced unrelated feelings and arousal levels in data disclosure decisions indicate that it is maybe not sufficient to protect internet users by only regulating the content and transparency, for example regarding organizations' data consent forms. It is known that it could be effective for users' protection to regulate the graphical representation, i.e., its visibility, of such a form, too (cf. Hendrickx et al., 1989; Tsai, Egelman, Cranor and Acquisti, 2011; Bornschein, Schmidt and Maier, 2020). Our results indicate that it could be beneficial to adapt regulations for the graphical representation of data consent forms by considering the feelings and arousal levels evoked (cf. Schaub, Balebako, Durity and Cranor, 2015; Kim et al., 2020). To prevent users from overdisclosure there could be distinct representations of a data consent based on users self-decided "feeling state": for instance, users with very positively valenced feelings could get displayed a certain form with especially calming colours. However, for legislators our study does not provide specific overdisclosure countermeasures. In this regard, our work rather serves as a thought-provoking impulse for lawmakers, in which way users could be protected from overdisclosure of personal data by displaying that also non-cognitive factors, such as unrelated feelings and arousal levels, impact users' disclosure willingness.

6 Appendix

Table 2. *Measurement items, Cronbach's α and Composite-Reliability for all constructs. Loadings of items are in brackets.*

Positively Valenced Unrelated Feelings (PVUF)	
Shortened from Klapwijk and Van Lange (2009); Cronbach's α : .81; Composite-Reliability: .86; 7-Point Likert scale with anchors 1 = "strongly disagree" and 7 = "strongly agree". <i>I feel right now:</i>	
PVUF1 (.8)	Happy
PVUF2 (.85)	Proud
PVUF3 (.9)	Enthusiastic
Arousal (AR)	
Shortened from Deng and Poole (2010); Cronbach's α : .84; Composite-Reliability: .9; 7-Point semantic differential with the following endpoints: <i>I am currently:</i>	
AR1 (.87)	unaroused - aroused
AR2 (.92)	calm - excited
AR3 (.82)	relaxed - stimulated
Willingness to Disclose and Participate in the Sweepstake (WDP)	
Adapted from Anderson and Agarwal (2011); Cronbach's α : .96; Composite-Reliability: .98; 7-Point semantic differential with the following endpoints: <i>To what extent would you be willing to participate in the raffle?</i>	
WDP1 (.97)	unlikely - likely
WDP2 (.98)	not probable - probably
WDP3 (.94)	unwilling - willing

Privacy Concerns (PC)	
Shortened from Hong and Thong (2013); Cronbach's α : .85; Composite-Reliability: .89; 7-Point Likert scale with anchors 1 = "strongly disagree" and 7 = "strongly agree".	
PC1 (.66)	It usually bothers me when companies/organizations ask me for personal information.
PC2 (.85)	I am concerned that companies/organizations would share my personal information with other companies/organizations without my authorization.
PC3 (.61)	I am concerned that companies/organizations do not devote enough time and effort to verify the accuracy of my personal information in their databases.
PC4 (.84)	I am concerned that companies/organizations do not devote enough time and effort to prevent unauthorized access to my personal information.
PC5 (.79)	It usually bothers me when I do not have control or autonomy over decisions about how my personal information is collected, used, and shared by companies/organizations.
PC6 (.76)	It usually bothers me when I am not aware or knowledgeable about how my personal information will be used by companies/organizations.
Perceived Benefit (BENE)	
Adapted from Voss, Spangenberg, & Grohmann (2003), Cronbach's α : .83; Composite-Reliability: .89; 7-Point Likert scale with anchors 1 = "strongly disagree" and 7 = "strongly agree"	
<i>The Bundesliga jerseys as prizes in the raffle I perceive as:</i>	
BENE1 (.82)	Functional
BENE2 (.84)	Practical
BENE3 (.74)	Necessary
BENE4 (.87)	Helpful
Perceived Privacy Risk (RISK)	
Adapted from Dinev, Xu, Smith, & Hart (2013), Dinev & Hart (2006), Featherman & Pavlou (2003); Cronbach's α : .94; Composite-Reliability: .95; 7-Point Likert scale with anchors 1 = "strongly disagree" and 7 = "strongly agree".	
<i>The Bundesliga jerseys as prizes in the raffle I perceive as:</i>	
RISK1 (.92)	It is very risky in this data collection to reveal personal information.
RISK2 (.93)	The disclosure of personal information in this data collection is associated with a high potential risk of losing privacy.
RISK3 (.9)	My disclosed personal information may be used improperly in this data collection.
RISK4 (.91)	The disclosure of personal information in this data collection could cause many unexpected problems.
Risk Probability (PROB)	
Adapted from Bolton, Cohen and Bloom (2006); Percentual slider scale from 0% - 100%	
<i>Please rate how likely you think it is that the information you disclosed in this sweepstake will be published on someone else's website, accessible to everyone?</i>	
Risk Severity (SEV)	
Adapted from Bolton et al. (2006); 7-Point semantic differential with 1 = "not at all serious" and 7 = "very serious".	
<i>Please rate how bad it would be for you if the data you disclosed in this sweepstakes were published on someone else's website, accessible to everyone?</i>	
SEV	unwilling - willing

Table 3. Age, sex, and group distribution in the sample.

	18-29		30-39		40-49		50-59		60+		Sum
	M	F	M	F	M	F	M	F	M	F	
"Happy" group	28	28	24	19	15	20	14	12	9	8	177
Control group	23	27	25	26	11	22	19	16	17	5	191
Sum	51	55	49	45	26	42	33	28	26	13	368

Table 4. Path Coefficient results.

Effect	Path Coefficient (Standard Deviation)	p-Value
AR -> BENE	.187 (.051)	.000
AR -> WDP	.08 (.044)	.07
AR -> PROB	-.014 (.06)	.815
AR -> RISK	-.012 (.041)	.766
AR -> SEV	-.037 (.053)	.48
BENE -> WDP	.416 (.047)	.000
PVUFxAR -> PROB	-.026 (.063)	.677
PVUFxAR -> BENE	.027 (.048)	.575
PVUF -> BENE	.232 (.049)	.000
PVUF -> WDP	.047 (.05)	.344
PVUF -> PROB	.014 (.056)	.809
PVUF -> RISK	-.023 (.046)	.619
PVUF -> SEV	-.047 (.056)	.405
PVUFxAR -> SEV	-.15 (.052)	.004
PVUFxAR -> RISK	-.078 (.039)	.045
PVUFxAR -> WDP	.102 (.038)	.007
PC -> WDP	-.017 (.056)	.755
PC -> RISK	.348 (.049)	.000
PROB -> RISK	.305 (.045)	.000
RISK -> WDP	-.184 (.056)	.001
SEV -> RISK	.178 (.048)	.000

Table 5. Loadings and cross loadings of the items.

Items	Constructs								
	PVUF	AR	PVUFx AR	PROB	SEV	PC	RISK	BENE	WDP
AR1	.052	.865	.133	.016	-.051	-.158	-.092	.181	.173
AR2	.030	.917	.185	-.056	-.077	-.121	-.101	.189	.202
AR3	-.135	.818	.130	.000	-.039	-.082	-.040	.113	.131
PVUF1	.796	-.181	.096	.009	-.056	-.073	-.051	.112	.070
PVUF2	.847	-.031	.002	.043	-.054	-.006	-.071	.185	.125
PVUF3	.899	.105	.112	-.016	-.049	-.062	-.030	.254	.189
WDP1	.169	.187	.196	-.142	-.083	-.177	-.292	.470	.972
WDP2	.165	.192	.198	-.145	-.091	-.185	-.275	.478	.978
WDP3	.145	.198	.193	-.176	-.106	-.228	-.322	.473	.944
BENE1	.185	.131	.085	-.101	-.051	-.093	-.187	.819	.366
BENE2	.221	.136	.049	-.068	-.107	-.141	-.216	.843	.414
BENE3	.151	.164	.040	.029	-.007	-.109	-.064	.737	.378
BENE4	.204	.193	.095	-.052	-.052	-.141	-.180	.869	.444
PVUFxAR	.083	.175	1.000	-.031	-.180	-.132	-.180	.083	.203
PC1	-.099	-.112	-.089	.160	.239	.656	.352	-.125	-.202
PC2	-.064	-.188	-.160	.213	.452	.847	.437	-.124	-.189
PC3	.022	-.015	-.034	.191	.289	.611	.363	-.066	.016
PC4	-.049	-.044	-.162	.213	.428	.836	.442	-.149	-.250
PC5	.004	-.157	-.045	.112	.405	.793	.379	-.076	-.082
PC6	-.036	-.122	-.070	.146	.357	.760	.370	-.120	-.162
RISK1	-.021	-.091	-.141	.395	.423	.464	.919	-.179	-.272
RISK2	-.014	-.107	-.156	.380	.411	.505	.931	-.151	-.283
RISK3	-.077	-.077	-.193	.397	.403	.461	.898	-.200	-.292
RISK4	-.094	-.073	-.168	.414	.383	.467	.910	-.202	-.277
SEV	-.061	-.067	-.180	.256	1.000	.485	.443	-.068	-.097
PROB	.011	-.019	-.031	1.000	.256	.231	.433	-.059	-.160

Table 6. Inner VIF values of the constructs.

Independent Variables	Dependent Variables				
	PROB	SEV	RISK	BENE	WDP
PVUF	1.007	1.007	1.011	1.007	1.067
AR	1.032	1.032	1.049	1.032	1.082
PVUFxAR	1.039	1.039	1.070	1.039	1.068
PROB			1.089		
SEV			1.374		
PC			1.353		1.389
RISK					1.420
BENE					1.138

Table 7. Heterotrait-Monotrait Ratio (HTMT) of the constructs.

	PVUF	AR	PVUFx AR	PROB	SEV	PC	RISK	BENE
AR	.175							
PVUFxAR	.091	.188						
PROB	.030	.030	.031					
SEV	.069	.070	.180	.256				
PC	.095	.167	.135	.250	.523			
RISK	.071	.101	.186	.449	.458	.584		
BENE	.260	.220	.090	.084	.073	.176	.224	
WDP	.169	.216	.207	.163	.098	.221	.324	.547

Table 8. Correlations between constructs and square root of the AVEs on the diagonal.

	PVUF	AR	PVUFx AR	PROB	SEV	PC	RISK	BENE	WDP
PVUF	.848								
AR	-.002	.868							
PVUFxAR	.083	.175	1						
PROB	.011	-.019	-.031	1					
SEV	-.061	-.067	-.18	.256	1				
PC	-.053	-.143	-.132	.231	.485	.756			
RISK	-.056	-.095	-.18	.433	.443	.519	.914		
BENE	.234	.192	.083	-.059	-.068	-.149	-.2	.818	
WDP	.165	.2	.203	-.16	-.097	-.204	-.307	.491	.964

Für unsere Forschung ist es wichtig, dass Sie sich in die folgende Situation hineinversetzen.

Bitte lesen Sie sich die folgenden Informationen und die dargestellte Situation genau durch, da Sie im Folgenden Fragen hierzu beantworten müssen.

Sie befinden sich in folgender hypothetischer Situation:

mingle weist Sie mittels der folgenden Nachricht auf ein Gewinnspiel hin:

Sie können an einem Gewinnspiel teilnehmen, bei dem Sie ein Fußballtrikot der 1. oder 2. Bundesliga Ihres Lieblingsvereins mit dem Flock Ihres Lieblingsspielers gewinnen können. Mehr Informationen finden Sie in dem hier verlinkten Instagram-Beitrag:

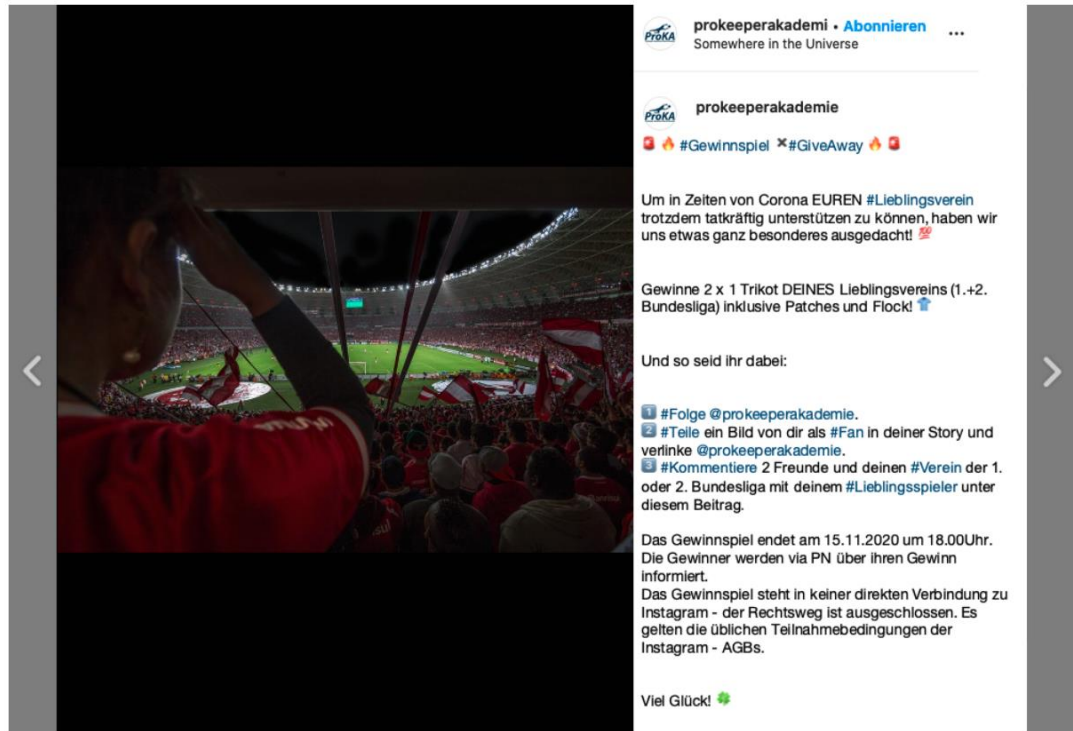


Figure 5. Scenario - Instagram sweepstake post.

Translation of the hypothetical situation:

“mingle informs you about a lottery by means of the following message:

You can participate in a sweepstake where you can win a 1st or 2nd Bundesliga soccer jersey of your favorite club with the flock of your favorite player.“

Translation of the displayed Instagram post:

“In order to be able to support YOUR favorite club in times of Corona, we have come up with something very special!

Win 2 x 1 jersey of YOUR favorite club (1.+2. Bundesliga) including patch and flock!

And this is how you are in:

1. #follow @prokeeperakademie.
2. share a picture of you as a #fan in your story and link @prokeeperakademie.
3. #comment 2 friends and your #club of the 1st or 2nd Bundesliga with your #favorite player under this post.

The sweepstake ends on 15.11.2020 at 6pm. The winners will be informed via PN about their prize.

The sweepstakes is in no direct connection with Instagram - the legal process is excluded. The usual conditions of Instagram - T&Cs apply.

Good luck!”

Der Beitrag gehört zur folgenden Instagram-Seite, auf diese werden Sie nach einem Klick auf das Bild in der Nachricht weitergeleitet:

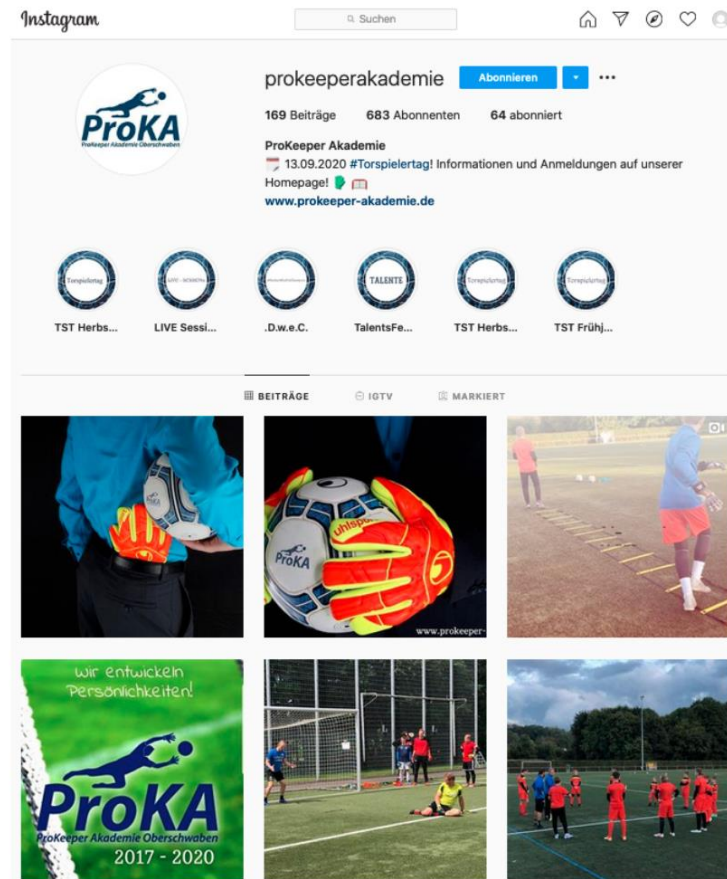


Figure 6. Scenario - Instagram account of the sweepstake organizer.

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