GOING TOO FAR? HOW CONSUMERS RESPOND TO PERSONALIZED ADVERTISING FROM DIFFERENT SOURCES

Freya De Keyzer
Department of Marketing
University of Antwerp
Prinsstraat 13, 2000 Antwerp, Belgium
School for History, Culture and Communication
Erasmus University Rotterdam
P.O. box 1738,3000 DR Rotterdam, the Netherlands
dekeyzer@eshcc.eur.nl

Guda van Noort
Amsterdam School of Communication Research
University of Amsterdam
P.O. Box 15791, 1001 NG Amsterdam, the Netherlands
G.vanNoort@uva.nl

Sanne Kruikemeier
Strategic Communication Group
Wageningen University & Research
PO Box 8130, 6700EW Wageningen, the Netherlands
sanne.kruikemeier@wur.nl

ABSTRACT

This paper examines the extent to which the level of personalization in advertisements on social networking sites from four online sources affects source attitudes. Based on the privacy-calculus theory, the trade-off between perceived personal relevance and perceived creepiness is tested. We also examine the moderating role of source type. We used a factorial survey by setting up a 3 (level of personalization: low vs. moderate vs. high) x 4 (source type: health vs. governmental vs. commercial vs. news) between-subjects design. We tested a moderated mediation model with perceived creepiness and relevance as competing mediating variables and source type as the moderating variable based on the privacy calculus theory and social exchange theory. The results indicate that perceived creepiness negatively explains personalization perceptions. The tipping point can be found between the low and moderate level: a moderate (vs. low) level of personalization increases perceived creepiness, but high personalization does not increase it further. Contrary to our expectations, perceived relevance does not act as a positive explanatory mechanism. Finally, our findings demonstrate that source type is important: the privacy calculus for each personalization level differs for different online sources.

Keywords: Personalization; Social networking sites; Privacy calculus; Source type; Vignette factorial survey

1. Introduction

The majority of online ads are now personalized towards individual Internet users (IHS Markit, 2017) due to new technologies and changes in the media landscape, such as widely applied algorithms, Artificial Intelligence (AI), and an upsurge of social media use, enabling the tracking and usage of consumer's online information (both personal and social). Especially, Social Networking Sites (SNSs) are an extremely important venue for personalized advertising practices because of their global adoption and the amount of personal information disclosed within these networks (De Keyzer et al., 2015; Kelly et al., 2017). It is often argued that advertising online will become even more personalized in the future (Kumar & Gupta, 2016; Schultz, 2016). Currently, the level of personalization used in advertising differs greatly; consumers can be addressed based on their name, browsing behavior, social ties, groups and preferences, and all possible combinations of such personal information (Arora et al., 2008; De Keyzer et al., 2022; Grubbs Hoy & Milne, 2010; Hawkins et al., 2008). In order to understand the implications of the algorithms used for personalization, we need to understand how people feel about them (Bucher, 2017) and whether they accept personalization (Wirtz et al., 2017). Although most people do not know precisely how such algorithms work, they try to make sense of them (i.e., so-called algorithmic imaginary; Bucher, 2017). Therefore, this study aims to investigate how social media users perceive personalized advertisements from algorithms using different types of personal data, and the resulting different levels of ad personalization.

The industry and scholars often assert that personalized advertising is – to some extent – more effective than non-personalized advertising (e.g., it is more memorable, attracts more attention, and sparks behavioral change; Malheiros et al., 2012; Matz et al., 2017; Noar et al., 2007). However, it is also found that personalized advertising may have a negative effect: personalized ads are perceived as creepy (Malheiros et al., 2012) or invasive (van Doorn & Hoekstra, 2013; White et al., 2008), and result in privacy concerns (Segijn & van Ooijen, 2022). This contradiction is also highlighted by Ur et al. (2012, p. 6), who argue that "taken as a whole, participants found online behavioral advertising[1] smart, useful, scary and creepy at the same time". Thus, while previous work has uncovered these contradictory feelings, three important gaps can be identified.

First, both beneficial and detrimental, underlying processes explaining the effectiveness of personalized advertising remain uncertain (Boerman et al., 2017). Positive consumer responses are usually explained by an increase in (perceived) relevance (De Groot, 2022; De Keyzer et al., 2022; Hayes et al., 2021), whereas negative responses are usually ascribed to a heightened level of privacy concern (Chellappa & Sin, 2005; Segijn & van Ooijen, 2022). This study extends previous work by deploying the privacy calculus theory to examine these competing responses to personalized advertising. This theory posits that consumers' decisions to disclose personal information are based on a cost-benefit trade-off (Culnan & Armstrong, 1999; Laufer & Wolfe, 1977). Studies have applied privacy calculus theory in the context of self-disclosure behavior (e.g., Culnan & Armstrong, 1999; Dienlin & Metzger, 2016; Laufer & Wolfe, 1977); however, privacy calculus might not only affect disclosure of personal information online but also affect other consumer responses such as attitudes towards the advertiser (Demmers et al., 2018). This study will build upon previous research that employed the privacy calculus in advertising research (e.g., De Keyzer et al., 2022; Youn & Shin, 2019) and examine the perceived benefits and the costs of personalized advertising in the context of social networking sites, and how their interplay affects source attitudes.

Second, this study examines two boundary conditions of the privacy calculus. A first boundary condition deals with the level of personalization. Previous research indicates that personalization techniques can result in "over-personalized" advertisements, referring to ads that become too personalized. In that case, the advertisement contains too much personal information to the extent that it becomes creepy (Gironda & Korgaonkar, 2018). Therefore, this study is also breaking new ground as it examines more closely the 'tipping point' of personalization. According to Malheiros (2014, p. 146), "advertisers should aim for sweet-spot personalization of ads", which refers to the level of personalization that maximizes the noticeability and users' comfort level with personalization. The current study sheds light on that sweet spot by examining the perceptions of three different personalization levels in one design.

A second boundary condition is context-dependency. Although previous research has indicated that consumer responses toward online behavioral advertising depend on the context (e.g., Smit et al., 2014), studies examining the effects of personalized content or advertising in different contexts are rare (see e.g., Bol et al., 2018; Smit et al., 2014; Ur et al., 2012). In line with previous suggestions made in the literature, we expect that in some cases (e.g., in news websites), personalization is more acceptable than in other cases (e.g., health websites), because consumers have learned that the use of personal information is appropriate in some contexts, but not in others (Acquisti et al., 2015). Therefore, the current study examines whether the perceptions of personalized ads are context-dependent by investigating the role of four different online sources. In sum, we examine competing underlying mechanisms and the boundary conditions of personalized advertising using a factorial survey design. We conclude with management implications and a future research agenda.

2. Personalized Advertising: Explaining Effects Using the Privacy Calculus Theory

In general, the privacy calculus theory is based on the idea that individuals are willing to give up part of their privacy in exchange for economic or social benefit (Culnan, 1993). Previous research on the privacy calculus theory has primarily focused on disclosing personal information (Acquisti et al., 2015; Bol et al., 2018; Dienlin & Metzger, 2016). The more benefits people expect from disclosing information, the higher the likelihood of disclosure (Laufer & Wolfe, 1977). The rewards that could be expected from disclosure include, for example, "social support, entertainment, tailored information, or monetary rewards." (Bol et al., 2018, p. 372), whereas risks could be "identity theft, reputational damage, or loss of control" (Bol et al., 2018, p. 372). A recent meta-analysis confirmed that costs such as privacy concerns or perceived risk negatively affect self-disclosure (Baruh et al., 2017).

1 Online behavioral advertising can be seen as a particular form of personalized advertising as it uses online behavior to generate a personal profile of a consumer, which later on can be used to personalize advertising.

The privacy calculus theory has also been applied to uncover why some studies have found beneficial effects of personalization, whereas others have found negative effects. For example, Demmers et al. (2018), Youn & Kim (2019), and De Keyzer et al. (2022) have applied the theory to advertising research. Users exposed to (personalized) advertising will perform a benefit-risk trade-off analysis (Youn & Shin, 2019), similar to when they are in a situation in which they need to decide to disclose personal information. The theory posits that consumers weigh the perceived benefits (e.g., perceived relevance) with the perceived costs (e.g., perceived privacy invasion; Culnan & Armstrong, 1999; Laufer & Wolfe, 1977). In case the benefits trump the costs, consumers will respond positively to personalized advertising. Based on the social exchange theory, we can expect consumers to build relationships with the brands they encounter on social networking sites, similar to other human relationships (Hayes et al., 2021). Each exchange between consumer and brand results in a benefit-risk trade-off whereby the expected value of the exchange is evaluated (Hayes et al., 2016). In order to maintain relational equity, the sender must provide beneficial information to the receiver (Hayes et al., 2016; Hsu & Lin, 2008). For example, when people are exposed to SNS advertisements that are more personalized based on personal data, these ads become more relevant and useful (De Keyzer et al., 2015). It also keeps these sites free for users to use (Kelly et al., 2017). Both arguments can be considered as benefits of personalized advertising.

Conversely, large amounts of personal information are collected via these sites, which can be considered a cost of personalized advertising (Gironda & Korgaonkar, 2018; H. Li et al., 2011), and this might increase feelings of creepiness (Malheiros et al., 2012; Segijn & van Ooijen, 2022; Ur et al., 2012). People are concerned about who is ‘snooping’ around in their personal social media profiles and what is known about them. Moreover, previous research indicates that personalized advertising increases privacy concerns due to the increased risk of data theft and misuse of personal information (Baek & Morimoto, 2012; Ham, 2016). In sum, although consumers seem to be concerned about their privacy when they encounter personalized advertising (Malheiros et al., 2012), they might, at the same time, appreciate the relevance and usefulness of personalized advertisements (Ur et al., 2012). These competing beliefs may override each other and, as a result, influence the outcomes of the privacy calculus (Dinev & Hart, 2006): some people might prefer personalized advertising as it increases relevance and decreases advertising clutter, but others might be too concerned about the invasion of their privacy.

Previous research has identified perceived relevance as a key benefit variable (De Groot, 2022; De Keyzer et al., 2022; Hayes et al., 2021). Consumers also mention it as the most important benefit of personalized advertising (Segijn & van Ooijen, 2022). Previously different cost variables have also been identified (e.g., reactance towards the ad, De Keyzer et al., 2022; perceived invasiveness, Niu et al., 2021; perceived intrusiveness, Pfiffelmann et al., 2020; ad avoidance, Youn & Kim, 2019). However, these variables can be considered primarily cognitive, whereas consumers’ perceptions might be formed affectively (De Keyzer, 2019). Therefore, it seems necessary in order to create a better understanding of personalization perceptions, to evaluate a more affective variable, such as perceived creepiness. Segijn & van Ooijen (2022) indeed indicate that negative affects are often mentioned by respondents as a cost of personalized advertising. Within the category of negative affect, creepiness is the most prominently mentioned category by respondents in their study. The following section reviews the literature regarding perceived creepiness and perceived relevance of the advertisement.

3. The Cost Side of Personalized Advertising: Perceived Creepiness

Creepiness refers to “anxiety aroused by the ambiguity of whether there is something to fear or not and/or by the ambiguity of the precise nature of the threat that might be present” (McAndrew & Koehnke, 2016, p. 10). As such, it is not the actual presence of danger that causes feelings of creepiness, but the uncertainty of danger being present or not (McAndrew & Koehnke, 2016). This perceived creepiness is also more and more used in non-psychological work, such as communication and marketing studies. In these fields, slightly different definitions have been used. For example, according to Malheiros et al. (2012, p. 581), perceived creepiness is “a sense that someone has been ‘snooping’ into a part of your life that should remain private.” Barnard (2014, p. 1) describes it similarly: “the marketer is watching her (ed. the consumer), and her privacy has been violated”. Moreover, Zhang & Xu (2016, pp. 1678–1679) state that, “[i]nstead of causing actual harms, in many privacy concerning cases, what novel technological features do is to trigger a sense of expectation violation or loss of control. In privacy research, creepiness is one particular emotional reaction to novel technological features, which is a mixture of fear, anxiety, and strangeness”. The underlying factor is the same: the uncertainty and unpredictability of behavior with which one is confronted.

Uncertainty is also prevalent when consumers are confronted with personalized advertising. Previous studies have found that consumers are uncertain of how personal data, used in personalized advertising, is collected (Malheiros et al., 2012; Ur et al., 2012), and how these data are used in algorithms, which results in feelings of creepiness (Bucher, 2017; Segijn & van Ooijen, 2022). People might wonder: ‘Is someone – or something – snooping around in my personal social media profile?’, ‘Are “they” following what I do on the Internet?’ and thus, ‘What do “they” know about me?' As a result, people express a need for consent to collect data about them (Malheiros et al., 2012). When they do not provide such consent, people feel uncomfortable, uncertain, and therefore perceive the personalized advertisement as creepy, especially when the level of personalization is too high (e.g., using a personal picture, Malheiros et al., 2012).

This perception of creepiness might result in what White et al. (2008) call personalization reactance. When the level of personalization is too high, consumers might react to it similarly as in the case of psychological reactance (Brehm, 1966). In such a case, consumers try to restore their freedom of choice and behave opposite to what is intended by the threat (Miron & Brehm, 2006). Therefore, they will try to resist the advertising message and respond negatively to it (van Doorn & Hoekstra, 2013; White et al., 2008). In our study, they might do this by evaluating the message source as less positive. A less positive evaluation of the advertisement is expected to lead to a less positive evaluation of the source, based on the well-established effect of attitude toward the advertisement on brand attitude (Homer, 1990). We expect that higher levels of personalization (i.e., using more detailed personal information) will make it more likely that an individual perceives personalized ads as creepier and, consequently, evaluates the source less positively. Therefore, we expect:

H1: (a) Higher levels of personalization result in higher levels of perceived creepiness of the advertisement, and (b) subsequently, into less positive source attitudes.

4. The Benefit Side of Personalized Advertising: Perceived Relevance

Previous studies suggesting a positive effect of personalization and ad responses propose personal relevance as an explanation. Several prior studies have established the mediating role of perceived relevance (e.g., De Groot, 2022; De Keyzer et al., 2022; Hayes et al., 2021). Consumers confronted with a persuasive message might try to relate the message to themselves, which is called self-referencing (Hawkins et al., 2008). This self-referencing is used as a heuristic cue or a decision aid. Due to limited mental resources, consumers construe a preference structure for self-referent content (Tam & Ho, 2006). For example, when the message is about women's apparel, most men would not relate to this message. Self-referent content, for instance personalized content, triggers selective processing, facilitating the construction of positive content evaluation. As a result, personalization could reduce decision time and information search efforts (Tam & Ho, 2006). Self-referencing could also motivate consumers to process the message more elaborately, which ultimately might lead to more positive evaluations of the message (Bright & Daugherty, 2012). As a result, this self-referencing can result in positive responses (Debevec & Romeo, 1992; Hawkins et al., 2008). For example, De Keyzer et al. (2015) found that even a basic level of personalization (based on gender) increases perceived relevance and results in a more positive attitude toward the source of the message (i.e., the brand). Therefore, we expect:

H2: (a) Higher levels of personalization result in higher perceived relevance of the advertisement, and (b) subsequently, more positive source attitudes.

In the two previous sections, we established that there might be two competing underlying mechanisms that are important when measuring the effects of levels of personalization on source attitudes. Previous work on the privacy calculus shows that these mechanisms work in competition but are weighted differently depending on the case or the context studied. For instance, Dienlin & Metzger (2016) found that with regard to self-disclosure in SNSs, the benefits outweighed privacy concerns, whereas, with regard to self-withdrawal, the privacy concern outweighed both privacy self-efficacy and the benefits. Also, Wang et al. (2016) show that in the context of mobile applications, the perceived benefits outweigh the perceived risks in predicting the intention to disclose personal information. In general, previous research indicates that both benefits and costs affect outcomes (Dienlin & Metzger, 2016). Because of conflicting findings on how the mechanisms compete, we propose the following research question for personalized advertising in social networking sites:

RQ1: Which mediating variable (i.e., perceived creepiness and perceived relevance of the advertisement) is stronger in explaining the effects of levels of personalization in advertising on source attitudes?

5. Investigating Boundaries: The Moderating Effect of Source Type

Most studies examining personalized advertising examine only one source, which is also often commercial (De Keyzer et al., 2022; Matz et al., 2017; Zarouali et al., 2018), without comparing with other sources (e.g., profit vs. non-profit brands). Nevertheless, the use of personal information is seen as appropriate in one context – of which a source is a part -, but unacceptable in another, as posited by Acquisti et al. (2015). Therefore, depending on the situation, people have different perceptions of how others – or, in this case, algorithms – handle their personal information. For example, in a study by Ur et al. (2012), participants were willing to allow data collection when reading the news, but not when searching for an STD treatment for a friend. Health-related information is seen as much more personal and therefore less appropriate for use in advertising than, for example, which news articles are read. This indicates that the same type of personal information (i.e., browsing history) could be perceived differently in various contexts and thus that personalization effects may differ in each context. Therefore, we expect that personalization through creepiness and relevance is moderated by the online source.

There is only some anecdotal evidence for the context-dependency of personalization effects: for example, Bol et al. (2018) find that personalization affected outcomes in a news and commercial context, but not in a health context. The following section gives a brief overview of studies examining personalization effects in these four contexts (health website, governmental website, online newspaper, and a commercial website) separately.

First, in a health context, it seems that the use of tailoring and personalizing persuasive health messages has a long history (e.g., Hawkins et al., 2008; Noar et al., 2009). These studies have often identified positive effects of personalization via relevance. As mentioned before, the use of personal information increases the likelihood of self-referencing, and as a result, increases perceived relevance. That, in turn, increases the processing of the message, leading to more positive consumer responses. However, there is also evidence that personalized health-related messages are perceived as embarrassing or too personal (Barnard, 2014), resulting in higher levels of reactance. Personal health information is very sensitive, and when this information becomes public, it might make consumers more prone to social judgment or sanctions (Weiss et al., 2006). As a result, when this information is used in personalized advertising, it increases the awareness that this information is public and increases negative feelings (e.g., perceived creepiness), and reduces positive feelings (e.g., perceived relevance).

Second, in the context of governmental communication, there has been little research on the use and the effects of personalization techniques. However, there is some research on the use of personalization by political parties. For example, Boerman & Kruikemeier (2016) found that a promoted tweet from a political party increased skepticism and negatively affected source attitudes, whereas this was not the case when a brand posted the tweet. The evidence here indicates that when a political party sends personalized advertisements, it is not welcomed by consumers. Boerman & Kruikemeier (2016) suggest that a politically promoted tweet is less often perceived as advertising, and therefore people need to activate their persuasion knowledge. In that case, they will try to react against the promoted tweet, leading to more negative outcomes such as a decrease in perceived trustworthiness of the source. As a result, we conclude that the personal nature of information in this context (e.g., voting behavior) is inappropriate in personalized advertising. Therefore, the perceived costs of personalization might affect the perceptions of the personalized advertisement more than the perceived benefits.

Third, news websites mainly use personalization to selectively distribute or show their news stories (Moeller et al., 2016). On the one hand, using this technique could increase the relevance of news items and thus positive attitudes. On the other hand, it creates the risk for 'filter bubbles', which means that consumers do not receive news that is not compliant with their interests and preferences (Moe & Schweidel, 2012; Pariser, 2012; Zuiderveen Borgesius et al., 2016). Nevertheless, Thurman et al.(2018) indicate that, collectively, people prefer algorithmic selection over editorial curation. Consumers appear to appreciate personalization algorithms in the context of news websites. Therefore, we conclude that the perceived benefits might trump the perceived costs in this context, increasing more positive attitudes towards the source of the personalized ads.

Fourth, personalization strategies have been used for a relatively long time in a commercial context and have become standard practice (Strycharz et al., 2019). As a result, consumers encounter personalized advertisements on social networking sites daily and might have grown accustomed to it. Although it appears to trigger positive effects via relevance (De Keyzer et al., 2022), there is also evidence that it might increase the perception of loss of information control (e.g., De Keyzer, 2019; Smit et al., 2014). In sum, in a commercial context, it remains unclear whether the perceived benefits or the perceived costs would have a stronger predictive power in affecting source attitudes.

In short, we expect that the privacy calculus is source dependent. Some types of personal information are considered less sensitive (e.g., previously read articles on a news website) than others (e.g., personal information in a health context). We have learned to keep health information private, and as a result, we consider it less appropriate to be used in personalized advertising. Consequently, we argue that the perceptions towards personalized advertising from different sources may lead to different outcomes. Therefore, we compare the personalization perceptions and competing mediating processes across four different sources: health, governmental, news, and commercial.

RQ2: Do different online sources (i.e., health, governmental, news, and commercial sources) moderate the relationship between different levels of personalization and source attitudes, mediated by perceived creepiness and perceived relevance of the advertisement?

6. Method

6.1. Study Design and Pretest

To test our conceptual framework (Figure 1), we have set up a 3 (personalization: low vs. medium vs. high) x 4 (source: health website, governmental website, online newspaper, and online store) between subject-factorial survey in which we exposed participants to different personalization scenarios. We exposed respondents to a short, carefully constructed description of a personalized advertisement on Facebook (vignette-based method; Atzmüller & Steiner, 2010). The use of vignettes is an established method with a long tradition in many areas, including sociology (Wallander, 2009), advertising (e.g., De Pelsmacker et al., 2019) and communication research (e.g., Kruikemeier et al., 2013). It allows for estimating unconfounded and context-dependent effects of explanatory factors (Atzmüller & Steiner, 2010). More specifically, vignettes allow researchers to inquire beyond specific circumstances (Schoenberg & Ravdal, 2000). Therefore, using vignettes allows for causal investigations of consumers' responses towards personalized advertising (Atzmüller & Steiner, 2010) regardless of specific contextual factors.

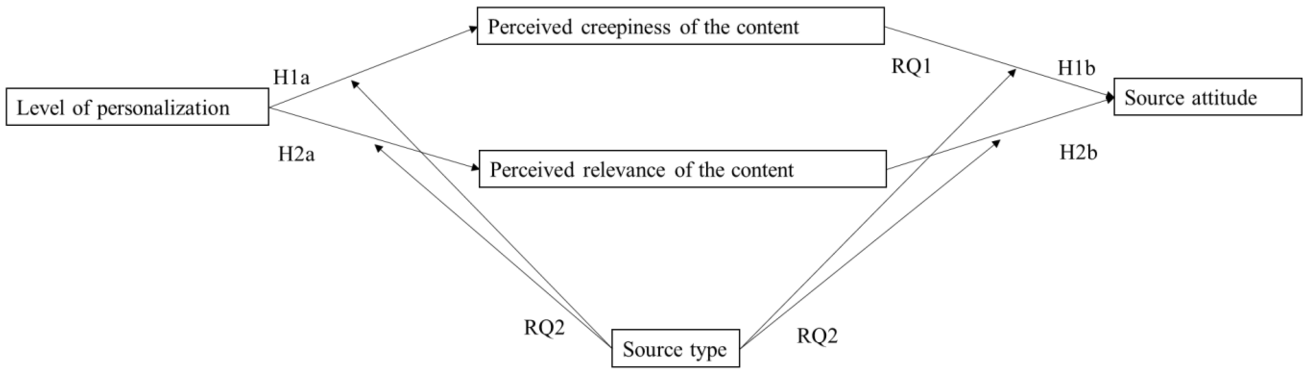


Figure 1: Conceptual Framework

To select the levels of personalization for our main study, in a pretest (N = 45, M_{age} = 21.24, SD_{age} = 1.52, 15.6% male), each respondent rated the level of personalization of five different vignettes. In total, we created 25 vignettes based on a study by De Keyzer (2019), which examines which cues increase perceived personalization. Respondents were instructed to imagine that they were visiting Facebook where they saw an advertisement that was based on, for example, their gender, interests, and friends' page-likes. Each vignette contained a maximum of three types of personal data (e.g., their gender, interest, and their friends' page-likes). Using a combination of personal data is a common technique to manipulate higher levels of personalization (e.g., Kaspar et al., 2019; Walrave et al., 2016; Zarouali et al., 2018). Respondents were students from a large Dutch university who received credit points for their participation. For a random set of five vignettes, participants were asked to rate on a seven-point scale (1 = strongly disagree 7 = strongly agree) to what extent the advertisement was personalized. Based on the findings of one-sample t-tests, we selected the use of page-likes of friends as the low personalized condition (M = 2.36, SD = .88), which was significantly lower than the mid-point of the scale (t (8) = -3.90, p = .005). Next, the page-likes of friends were combined with the use of the respondents' gender in the medium personalized condition (M = 3.18, SD = .89) because this condition was not significantly different from the midpoint of the scale (t (9) = -1.15, p = .278). Finally, in the high personalized condition, the page-likes of friends and gender were complemented using the respondent's interests (M = 4.85, SD = .96) because this combination resulted in a significantly higher perceived personalization than the midpoint of the scale (t (9) = 4.45, p = .002).

6.2. Procedure

In the actual study, we focused on Facebook because it is a popular social network site today in terms of users (Statista Inc., 2021). We created twelve vignettes (3 personalization levels x 4 online sources) to cover our design. Participants (N = 619, M_{age} = 45.73, SD_{age} = 15.59, 52.2% male) were recruited via a Panelclix' panel in the Netherlands and randomly assigned to one of the conditions. Panelclix sent out invitations to participate via email, and participants were compensated with points that can be converted into monetary compensation. The sample was representative of the overall targeted population. Only participants with a Facebook account were selected; 65.9% of the respondents spent time on Facebook every day. Only 3.9% of the respondents had less than 11 Facebook friends, and 10.5% of respondents reported having more than 400 friends. Respondents first answered questions regarding their Facebook use: the number of Facebook friends and number of days spent on Facebook in the past week. Before reading the vignette, participants were instructed to imagine the scenario as vividly as possible. All vignettes were similar to the vignettes used in the pretest, except for the specific source that was added in the text by mentioning, for example, that the advertisement was "for a health website, like gezondheidsplein.nl or thuisarts.nl" (see Appendix A). After first measuring perceived creepiness, perceived relevance, and source attitude, participants were debriefed and thanked for their participation.

Table 1: Measures Used in Study

Constructs	Items	Mean (SD)	Factor Loadings	Cronbach's α	Composite reliability	AVE
Number of FB friends	How many Facebook friends do you have in total? (if you are unsure, please make an estimation)	189.63 (360.51)	-	-	-	-
Days spent on FB	In the past week, how many days have you used Facebook?	5.92 (1.78)	-	-	-	-
Perceived creepiness of the advertisement	To what extent do you think the advertisement from the story was: 1) Creepy 2) Disturbing 3) Worrying	2.39 (1.62)	.952 .943 .949	.944	.964	.898
Perceived relevance of the advertisement	What do you think about the advertisement from the story? The advertisement was: 1) Not important – Important 2) Not relevant – relevant 3) Meaningless - Meaningful	2.99 (1.63)	.952 .952 .955	.949	.967	.908
Source attitude	The (health website), like example 1 and example 2, from the story is: 1) Unattractive – Attractive 2) Bad – Good 3) Unpleasant – Pleasant 4) Unfavorable - Favorable	4.04 (1.35)	.926 .935 .953 .934	.954	.966	.878

6.3. Measures

Perceived creepiness. Perceived creepiness was measured with three items: "To what extent do you think the advertisement was 1) creepy, 2) disturbing, 3) worrying." adapted from Zhang & Xu (2016) on a scale from 1 = totally disagree to 7 = totally agree ($M = 2.39$, $SD = 1.42$; $\alpha = .944$).

Perceived relevance. Perceived relevance was measured with three items: "What do you think about the advertisement from the story. The advertisement was: 1) not important – important, 2) not relevant – relevant, 3) meaningless – meaningful." from De Keyzer et al. (2021) on a bipolar semantic differential from 1 to 7 (M = 2.99, SD = 1.63; α = .949).

Source attitude. Source attitude was measured with four items: "The (health website/governmental website/online newspaper/commercial website), like (example 1) and (example 2) from the story is 1) unattractive – attractive, 2) bad – good, 3) unpleasant – pleasant, 4) unfavorable – favorable." on a seven-point semantic differential (M = 4.04, SD = 1.34; α = .954; Spears & Singh, 2004).

Descriptive variables. The number of Facebook Friends was measured with one item: "How many Facebook friends do you have in total?". Days spent on Facebook were measured with one item: "In the past week, how many days have you used Facebook?".

7. Results

7.1. Confirmatory Factor Analysis

To examine discriminant validity between our three variables. We first performed a confirmatory factor analysis (CFA) using SmartPLS 3 on the mediating and dependent variables (i.e., perceived creepiness, perceived relevance, and source attitude). Indices of model fit indicate an acceptable fit of the CFA model (SRMR = .034, χ^2 = 431.388, NFI = .935). After inspecting the factor loadings, we can confirm convergent validity: the factor loadings for all indicators were large and significant (Table 1). Moreover, the average variance extracted (AVE) for each factor was above the .50 threshold.

Furthermore, reliability estimates range between .964 and .967, which are well over the recommended .70 (Hair et al., 2014). In Table 2, the diagonal shows the square root of the AVE per construct, and the off-diagonals show the correlation between each pair of constructs. No correlation was higher than the square root of the AVE, confirming discriminant validity (Fornell & Larcker, 1981). Moreover, Table 2 shows that the average shared variance is larger than the maximum shared variance. Thus, we can confirm discriminant validity (Hair et al., 2014).

Table 2: Square Root of Average Variance Extracted and Correlations per Factor

	Perceived creepiness of the advertisement	Perceived relevance of the content	Source attitude
Perceived creepiness of the advertisement	**.948**		
Perceived relevance of the advertisement	-.201	**.953**	
Source attitude	-.305	551	**.937**

Note: The square root of average variance extracted (AVE) can be found in bold on the diagonal, and the correlations are in the off-diagonals.

7.2. Hypotheses Testing

Structural Equation Modeling (SEM) in SmartPLS 3 was used to test the mediation hypotheses and answer the research questions. Indices of model fit indicate an acceptable fit of the structural model (SRMR = .0059, χ^2 = 389.713, NFI = .943). In the first step, the level of personalization was entered as two independent dummy variables. First, we ran the analysis with medium and high personalization, using low personalization as the reference category. Second, we ran the analysis with low and high personalization, using medium personalization as the reference category.

Perceived creepiness and perceived relevance were included as mediating variables. Source attitude was entered as the dependent variable (Table 3). Days spent on Facebook and number of Facebook friends were entered as covariates[2]. In a second step, the online source (health, governmental, news, commercial) was entered as a grouping variable for the multi-group comparison (Figure 3).

[2] In order to check the robustness of the model, the covariates were also entered as separate moderating variables. Days spent on FB does not act as a moderating variable, whereas number of FB friends weakens the effect of a moderate level of personalization (compared to low level) on relevance (β = -.091, p = .043) and the effect of creepiness on brand attitude (β = -.131, p = .040).

Table 3: Path Coefficients

	Reference category: Low level of personalization		Reference category: Moderate level of personalization	
	Path coefficient	p-value	Path coefficient	p-value
Low level of personalization → Perceived creepiness of the advertisement	-	-	-.154	.001
Low level of personalization → Perceived relevance of the advertisement	-	-	.133	.003
Moderate level of personalization → Perceived creepiness of the advertisement	.157	<.001	-	-
Moderate level of personalization → Perceived relevance of the advertisement	-.136	.003	-	-
High level of personalization → Perceived creepiness of the advertisement	.210	<.001	.055	.236
High level of personalization → Perceived relevance of the advertisement	-.057	.218	.077	.113
Perceived creepiness of the advertisement → Source attitude	-.204	<.001	-.204	<.001
Perceived relevance of the advertisement → Source attitude	.516	<.001	.516	<.001
Days spent on FB → perceived relevance of the advertisement	.066	.003	.115	.005
Days spent on FB → perceived creepiness of the advertisement	-.043	.239	-.048	.264
Days spent on FB → source attitude	-.031	.401	-.031	.379
Number of FB friends → perceived relevance of the advertisement	.115	.196	.066	.206
Number of FB friends → perceived creepiness of the advertisement	-.048	.131	-.043	.146
Number of FB friends → source attitude	-.017	.699	-.017	.685

First, we expected that higher levels of personalization would increase perceived creepiness (H1a) and subsequently resulted in less positive source attitudes (H1b). The findings show that a moderate level of personalization does increase perceived creepiness ($\beta = .157$, $p < .001$), and a high level increases it even more ($\beta = .210$, $p < .001$) compared to a low level of personalization. A high and moderate level of personalization do not significantly differ in perceived creepiness ($\beta = .055$, $p = .236$). H1a is thus partially supported. The findings also confirmed that an increase of perceived creepiness decreases source attitude ($\beta = -.204$, $p < .001$). H1b is therefore supported. This is also demonstrated in Figure 2. For the indirect effects of the levels of personalization through perceived creepiness, we find a negative, significant indirect effect of a moderate level of personalization ($\beta = -.032$, CI = [-.053; -.015], $p = .001$) and of a high level of personalization ($\beta = -.043$, CI = [-.066; -.021], p = <.001) compared to a low level, but not of a high level of personalization in comparison with a moderate level of personalization ($\beta = -.011$, CI = [-.035; .006], $p = .268$). These findings thus indicate that the tipping point for creepiness is between a low and a moderate level of personalization: increasing the level of personalization from moderate to high does not increase feelings of creepiness further. Moderate and high levels of personalization are perceived as creepier, resulting in more negative source attitudes than the low level of personalization.

Second, we expected that higher levels of personalization would increase perceived relevance (H2a) and subsequently resulted in more positive source attitudes (H2b). Contrary to what we expected, a moderate level of personalization decreased perceived relevance ($\beta = -.136$, $p = .003$), and a high level of personalization did not significantly influence perceived relevance ($\beta = -.057$, $p = .218$) compared to a low level of personalization. High and moderate levels of personalization did not differ in perceived relevance ($\beta = .077$, $p = .113$). Therefore, H2a is not confirmed. However, our results support H2b: a higher level of perceived relevance leads to a more positive source attitude ($\beta = .516$, $p < .001$). This is also demonstrated in the indirect effects of personalization through perceived relevance: we only found one significant indirect effect. A moderate level of personalization has a negative, significant indirect effect ($\beta = -.070$, CI = [-.116; -.025], $p = .004$) compared to a low level of personalization, but not for a high level compared to a low level ($\beta = -.029$, CI = [-.074; .018], $p = .220$) nor compared to a moderate level ($\beta = .040$, CI = [-.008; .087], $p = .113$). This means that our findings do not support the notion that perceived relevance is a positive explanatory mechanism of personalization effects on source attitude.

Table 4: Results from ANOVA

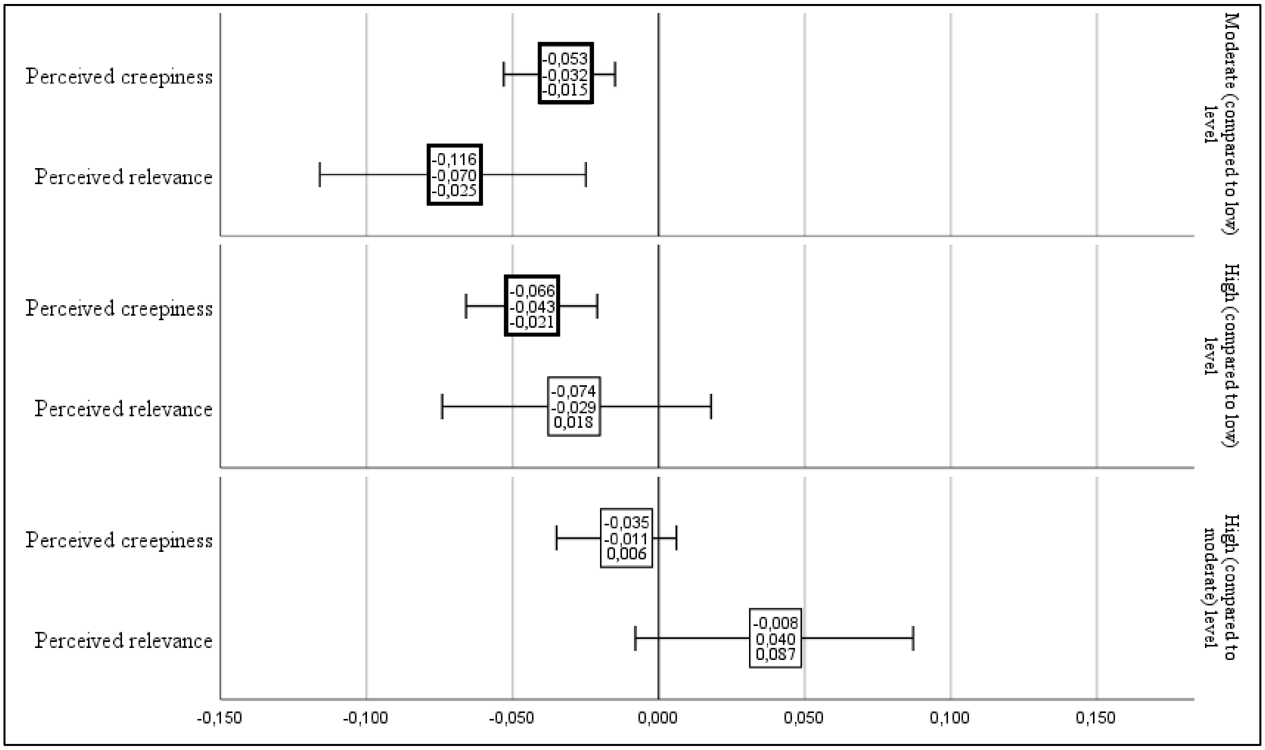
	Perceived creepiness of the advertisement		Perceived relevance of the advertisement	
	Mean	SD	Mean	SD
Low level of personalization	1.97	1.38	3.21	1.62
Moderate level of personalization	2.49	1.68	2.76	1.55
High level of personalization	2.69	1.69	3.02	1.70

To support the interpretation of the results, we conducted an ANOVA with personalization as the independent variable and perceived creepiness and perceived relevance as the dependent variables. Similar to the structural equation model, the ANOVA shows a significant difference between the three levels of personalization in perceived creepiness ($F(2, 616) = 11.063$, $p < .001$) and in perceived relevance ($F(2, 616) = 4.045$, $p = .018$). Moreover, posthoc tests show that the low level of personalization is significantly less creepy than the moderate level ($p = .002$) and less creepy than the high level ($p < .001$). The perceived creepiness is not significantly different between the moderate and the high level of personalization ($p = .645$). Moreover, the low level of personalization is significantly more relevant than the moderate level of personalization ($p = .012$), but not significantly different from the high level ($p = .577$). The moderate level of personalization is also not significantly different from the high level of personalization ($p = .281$). The means and standard deviations are presented in Table 4.

For our first sub-question, we wondered which mediating variable was stronger in explaining the effects of levels of personalization on source attitude. We can be short in answering this question because perceived relevance did not positively explain personalization effects. This means that perceived creepiness (compared to perceived relevance) was a negative and stronger predictor of personalization for all three levels.

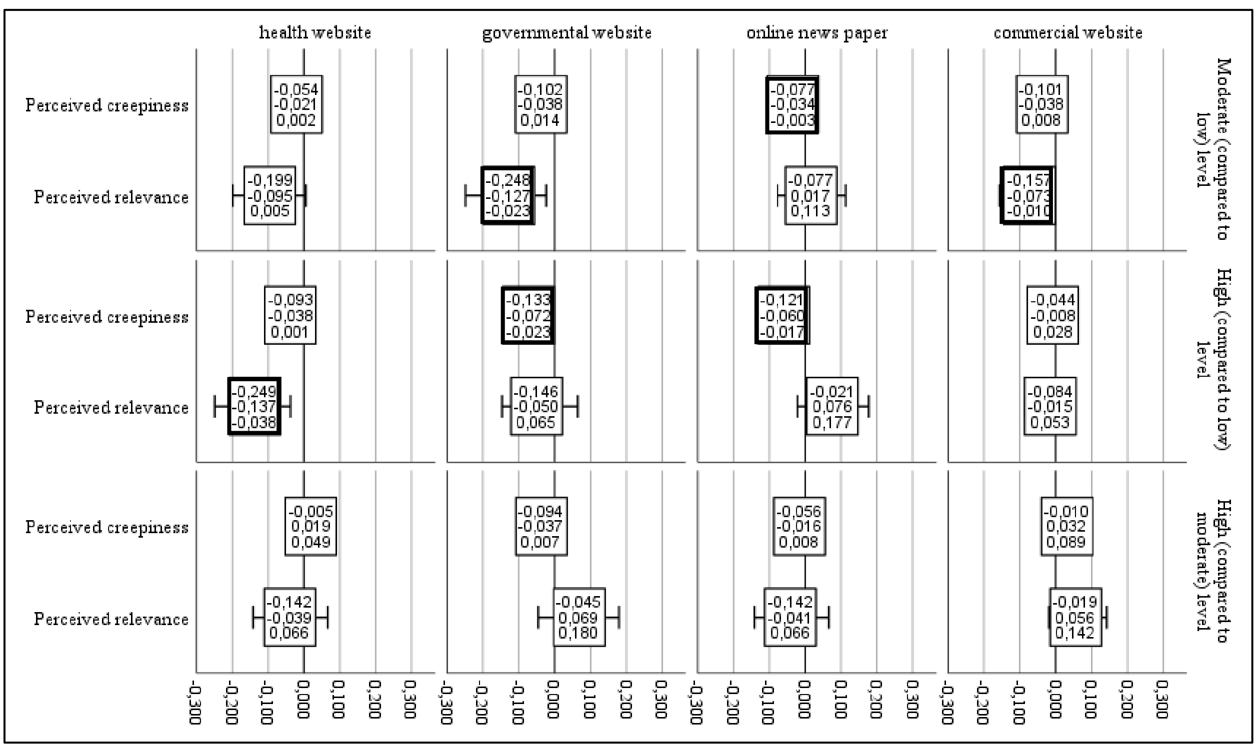
For our second sub-question, we wondered to what extent the different sources moderate the relationship between levels of personalization and source attitude, mediated by perceived creepiness and perceived relevance of the advertisement. Therefore, in a second step, we entered the online source type as a grouping variable to examine whether the explanatory power of the mediating variables differs between the various online source types (see Figure 3). When considering the different sources, the previously discussed patterns for perceived creepiness (as a negative explanatory mechanism) and perceived relevance (as a non-significant mediating principle) remain the same, but mainly when comparing high and low levels of personalization (and not comparing low and moderate levels). In the row 'High (compared to low) level column' in Figure 3, we see that perceived creepiness is a negative explanatory mechanism for a governmental website and an online newspaper. When comparing the low and moderate levels of personalization, this pattern was also found for an online newspaper. Interestingly, perceived creepiness does not explain the effect on attitude towards the health or commercial source (i.e., online store).[3]

[3] The full regression results in Appendices B and C indicate that the source primarily affects the relationship between the level of personalization and the mediating variables, perceived creepiness and perceived relevance of the advertisement, but not the relationship between the mediating variables and the dependent variables, source attitude.



Notes: The boxes show 1) ULCI, 2) path coefficient and 3) LLCI. Significant indirect effects in bold.

Figure 2: Bootstrap Intervals of Specific Indirect Effects of Levels of Personalization



Notes: The boxes show 1) ULCI, 2) path coefficient and 3) LLCI. Significant indirect effects in bold.

Figure 3: Bootstrap Intervals of Specific Indirect Effects of Levels of Personalization for each Source Type

8. Discussion

Previous research indicates that people are unaware of which personal data is collected about them or how it is collected (Bucher, 2017). People do not even understand how algorithms use this personal data to personalize advertising on, for example, social networking sites. Nevertheless, when using social networking sites, users are confronted with personalized advertisements. The current study examines the implications of that by investigating the tipping point of personalization: according to consumers, when do advertisers go too far in personalizing the advertisements they provide? Moreover, the study examined whether this ultimately leads to negative attitudes towards the source of the ads. We tested the influence of three different levels of personalized advertising on source attitude to examine this tipping point. Using the privacy calculus model (e.g., Culnan & Armstrong, 1999; Dienlin & Metzger, 2016; Laufer & Wolfe, 1977) and the social exchange theory (Hayes et al., 2016) , the current study aimed to examine two competing mechanisms (i.e., perceived creepiness and perceived relevance) that mediate the effect of different levels of personalization on source attitude. Furthermore, based on the notion of context-dependency of Acquisti et al. (2015) we proposed and tested how such effects differ across four online sources reflecting different contexts (health website, governmental website, online news website, and an online store).

In general, our findings suggest that higher levels of personalization do indeed increase perceived creepiness. More specifically, our results indicate that the sweet-spot, or tipping point, of personalization, is found already between a low and moderate level. Increasing a low to a moderate level increases perceived creepiness, but a high personalization levels does not increase it further. This might result from the fact that social network site users might not be aware that so much information is gathered about them and can be used in advertising. As a result, when confronted with the use of this personal information in an advertisement, they might feel as if someone has been ‘snooping’ around in their personal profile or their surfing behavior, leading to perceptions of creepiness, which is in line with, for example, Malheiros et al. (2012) and Ur et al. (2012). This increase in creepiness leads to less positive attitudes toward the source whichis in line with what White et al. (2008) have called ‘personalization reactance’. When consumers feel threatened by someone or something examining their personal information, they will react to this threat by, for example, behaving opposite to what is intended by the threat.

Contrary to our expectations, perceived relevance does not significantly change when going from a low level or a moderate level of personalization to a high level, but it does, contrary to our expectations, decrease when going from a low level to a moderate level. One potential reason is that, in line with the personalization reactance (White et al., 2008), respondents respond negatively towards higher levels of personalization or even act in the opposite direction of the intended behavior. As such, when confronted with a persuasive message that is too personal, consumers might feel they are being persuaded and react against it (Brehm, 1966). In line with that, consumers might activate their persuasion knowledge more easily when confronted with more personalized persuasive messages (Eisend & Tarrahi, 2022; Friestad & Wright, 1994). The activation of persuasion knowledge, in turn, can result in reactance towards the persuasive message (Friestad & Wright, 1994). Another potential reason for the lack of support for H2 could be found in the findings of Li (2016), who posits that actual personalization, which in our study is operationalized by combining up to three personalization elements (i.e., friends’ page-likes, gender and interests), does not automatically yield favorable perceptions. The perception of personalization (i.e., a consumers’ perception of how adapted the advertisement is to their personal profile) has been proven to be a consistent predictor of perceived relevance (De Groot, 2022; De Keyzer et al., 2022). As such, as De Keyzer (2019) argues, even though many different personalization elements (i.e., personal data) can elicit a perception of personalization, this does not automatically lead to downstream effects. For example, in De Keyzer (2019) the use of location in personalized advertising was perceived as annoying. Although it does elicit the perception of personalization, consumers might not perceive a personalized advertisement as positive.

In short, an increase in perceived relevance increased the attitude toward the source, however, we cannot conclude that perceived relevance positively explained personalization effects on source attitudes. This means that perceived creepiness was a stronger explanation for personalization effects. Our findings seem to suggest that the perceived costs outweigh the perceived benefits. Nevertheless, due to the insignificance of the indirect effects via perceived relevance of the advertisement this evidence is not irrefutable to clearly establish whether the perceived costs or the perceived benefits of personalized advertising are the strongest. In sum, future research is needed to flesh out the underlying mechanisms of the perceptions towards personalized advertising.

Finally, we examined whether different sources, reflecting distinctive contexts, moderated the effects on source attitude via perceived creepiness and perceived relevance. Our findings suggest that there are indeed differences between sources. The negative effect of personalization through perceived creepiness holds for governmental sources and for an online newspaper, which is in line with expectations. Consumers appear to find it inappropriate for these sources that personal information is being used in advertising messages. Interestingly, this pattern does not occur within a health and commercial context, that is, for health website and online stores. In these contexts, creepiness does not seem to play a role. When speculating on the underlying reason for these effects, the persuasion knowledge model (Friestad & Wright, 1994) might provide interesting insights. In some contexts (governmental website and a news website) it might be more difficult to recognize the persuasive intent of the message. As such, the activation of persuasion knowledge takes more effort, which in turn, could result in reactance toward the advertisement. In a similar vein, because consumers might have grown accustomed to receiving highly personalized messages from commercial sources (De Keyzer et al., 2022), they might need less effort to recognize them as persuasive. Given that commercial messages are typically designed to create favorable responses, they do no necessarily lead to negative perceptions. For the health website, the underlying reasoning might not be related to persuasion knowledge, but to the sensitivity of the topic. The use of personal information might become embarrassing, too personal or inappropriate, which could result in feelings of creepiness.

Looking at the covariates, in a commercial context, when confronted with a personalized advertisement, consumers who spend more time on Facebook indicate higher levels of perceived relevance and lower levels of perceived creepiness. Given the exploratory nature of these findings, more in-depth examinations in these effects are indispensable. Again, the activation and use of persuasion knowledge (Friestad & Wright, 1994) in these different contexts could help understanding these findings. When consumers are more accustomed to personalized advertising, their persuasion knowledge will more likely be activated since they can more easily recognize it (e.g., Eisend & Tarrahi, 2022). As such, they might understand how the personal information ended up being used in the advertisement, resulting in a lower perception of creepiness and, therefore, a stronger feeling of relevance. On the other hand, when consumers are less accustomed to personalized advertising, the response to the activation of their persuasion knowledge might be a stronger feeling of creepiness and as such a stronger reactance towards the advertisement.

In the commercial context, the covariate 'Days spent on Facebook' has a significant effect on perceived creepiness (and perceived relevance): users who use Facebook perceive the personalized advertisements as less creepy and more positive. This finding is in line with De Keyzer et al. (2015), who report a more positive consumer response to personalized advertising when the user has a more positive attitude toward the social networking site. In sum, this means that personalization effects and the privacy-calculus theory are context-dependent.

9. Theoretical and Practical Implications

Our results have several important implications. A first theoretical implication is that our findings suggest that the privacy calculus applies to self-disclosure behavior (Demmers et al., 2018) and to other important online consumer responses, that is, the evaluation of the source of the message. There appears to be some relation between how consumers believe they should behave (self-disclosure) and how they evaluate sources of personalized advertising. Our findings suggest that the perceived benefits of personalized advertising do not seem to trump the perceived costs of personalized advertising in the context of social networking sites. This means that even though previous research has concluded that consumers seem to appreciate personalized advertisements (Ur et al., 2012), our findings suggest that they are primarily creeped out. More specifically, we looked for the sweet spot of personalized advertising: when does personalization come too close? Our findings indicate that, in general, this is already at the low level: increasing the level of personalization increases creepiness significantly while it does not increase perceived relevance. This means that using a low level of personalization seems to creep out consumers the least and increasing the level to even a moderate level already significantly increases creepiness. In line with Malheiros et al. (2012) and Ur et al. (2012), we found that perceived creepiness negatively affects source attitudes. This indicates that when personalization goes too far for consumers, they will evaluate the source as less positive. Finally, we examined the moderating effect of source type. In line with Acquisti et al. (2015) and Nissenbaum (2010), we find that the tipping point of personalization is context-dependent. The negative effect of personalization through perceived creepiness only occurred in a governmental and online news context, but not in a health or commercial context. This indicates how the interplay between the perceived benefits and risks of personalized advertisements differ in specific situations. Especially in situations where the stakes are higher, and people might less likely be accustomed to personalized advertising, people consider the risks more important.

Our findings also have far-reaching practical implications. On the one hand, our findings indicate that personalized advertising on SNSs already appears to be perceived as creepy by consumers when it is moderately personalized, leading to less positive consumer responses. On the other hand, relevance did not increase with the level of personalization. In general, it is, therefore, best to use only a low level of personalization. Examining the effects separately for the four different source types helped to clarify these effects. In a health and commercial context, the level of personalization does not matter as higher levels are not perceived as creepier. However, for other contexts (governmental and news), one should be careful with personal data usage for personalization. Especially higher levels of personalization are perceived as creepy and negatively affect how consumers evaluate the source. This means that in these contexts, personalization might negatively affect the brand through creepiness. As brand responses are strongly related to all kinds of consumer responses - also responses that are specifically important in online and social media platforms (i.e., engagement, reference) - personalization should be handled with care. At the same time, we do not find positive effects through perceived relevance of a higher level of personalization for a health or commercial context. This means that these sources possibly do not monetize on personalization efforts in social media advertising.

10. Agenda for Future Research

The limitations and findings of this study provide opportunities for future research. In the current study, respondents were exposed to a vignette asking them to imagine a situation where they encountered a personalized advertisement. Although a vignette approach is common (e.g., De Pelsmacker et al., 2019; Kruikemeier et al., 2013) and suitable for the current research aims (i.e., investigating personalization perceptions across contexts) as it allows for the estimation of unconfounded and context-dependent effects of explanatory factors (Atzmüller & Steiner, 2010; Schoenberg & Ravdal, 2000), this approach comes at the expense of external validity. Therefore, future research could adopt a different design to test the perceptions of different levels of personalization (or different combinations of personalization elements) in ads of different actual organizations.

The use of actual materials will also allow the use of visuals which relies less on consumers memory. Since the increase of perceived relevance by low levels of personalization was unexpected, future research is suggested to delve deeper into the boundary conditions of the effect of personalization on perceived relevance. For example, we found some indication that days spent has an impact on perceived relevance and believe this could be an interesting avenue to explore. However, to obtain more fine-grained understanding, we would suggest to not (only) look into the number of days users spent on their social media but rather look at how long they spent. Moreover, we have now used a self-reported measure whereas digital trace data could be a more accurate representation of time spent (e.g., Verbeij et al., 2021). Other interesting boundary conditions could lie in the different backgrounds of users. In line with the Persuasion Knowledge Model (Friestad & Wright, 1994), it could be expected that respondents with more experience using a social media platform are more used to personalized advertising, which could result in higher levels of persuasion knowledge. The activation of persuasion knowledge can, in turn, result in more recognition of the persuasive intent (Eisend & Tarrahi, 2022) or in different downstream effects.

Moreover, to avoid confounds between contexts and sources, materials can be created for multiple brands or organizations for each context stimuli. Such organizations should then also be pretested on pre-existing attitudes to avoid a confound between context and the outcome variable. Furthermore, an alternative research design could further investigate and establish the causal relationship between the mediating variables and outcome variables. Specifically, a manipulation-of-mediation design could be used. By using a manipulation-of-mediation design could then prevent potential interplay between the mediating factors. However, these types of experiments do not come without their own challenges (see Pirlott & MacKinnon (2016) for a detailed discussion). This design would also overcome potential issues with measurement order: in our study, the mediating variables were measured before the dependent variable due to temporal precedence (Pirlott & MacKinnon, 2016). Theoretically, source attitude succeeds the mediating variables, perceived creepiness, and perceived relevance. However, it is not unimaginable that the mediating variables themselves might have affected the responses to the dependent variables. Therefore, based on Geuens & De Pelsmacker (2017), future research could measure the mediating variables after measuring the dependent variables. Future research could also randomize the order of the mediating variables and the dependent variables to avoid a question order bias. These research designs could also enable future research to examine multiple mediating variables. The current study reports a 3 x 4 factorial survey with two different mediating variables and, as such, already reports a complex design. However, additional potential mediating variables (e.g., reactance toward the advertisement or perceived intrusiveness) have been found to mediate the relationship between personalized advertising and source attitudes and could, therefore, be considered. Moreover, the role of persuasion knowledge could be explored as they might help understand the context-dependency of the different levels of personalization.

Moreover, our study only used self-reported attitudes and did not measure actual behavior (e.g., click-through rates, engagement responses, or sales). Future research could extend our findings by adopting other measures to examine the perceptions. For example, current data analyzing techniques allow researchers to analyze actual social network data and its impact on click-through rates, or even purchases (Leong et al., 2018). Such measures and real-world data might be a venue for future research. Nevertheless, self-reported measures are standard in survey research for reasons of internal validity (as was the case in our factorial survey where respondents were presented with examples of real brands) or when people are confronted with fictitious brands (Geuens & De Pelsmacker, 2017) Also, when analyzing real social network data, it becomes difficult to compare personalized advertising messages and their effects because they might differ on more aspects than merely their level of personalization and the source. Therefore, internal validity would be compromised. Moreover, behavioral data is not always suitable to test personalization effects: When real-world behavioral data are examined, one should consider whether the purpose of the personalized messages of which the behavioral outcomes are examined are in fact aimed at behavioral change (such as clicks and likes) or other persuasive outcomes (such as brand promotion and reputation).

Next, our study has focused on the source to examine the context-dependency of personalized advertising. We believe that future research should dig into the differences between the different sources and further determine the boundary conditions of personalization effects. Future work could examine what personal information is considered inappropriate to use in personalized advertisements, depending on the source of the advertisement. Furthermore, as we did not find significant indirect effects for the online store or the health website, future research is encouraged to investigate what exactly drives source attitudes in the contexts when using personalized social media advertising. One interesting avenue to look into could be the use of persuasion knowledge (Friestad & Wright, 1994) for these different contexts. The activation of persuasion knowledge might be different depending on the context of the advertisement, and, as such result in different perceptions of the personalized advertising.

Furthermore, our study focused on one aspect of the context (i.e., the source). However, other contextual variables could be examined in future research. For example, the social media platform and the content or theme of the message could also affect consumers' responses to personalized advertising. Examining our covariates, the relationship consumers have with the platform seems interact with how they perceive personalized advertising on these platforms. Voorveld (2019), for example, argues that consumer responses to brand communication in different social media platforms differ. The platform can also be used as a source of information in the processing of personalized advertising. As such, we encourage future research to compare the perceptions of personalized advertising between different social media platforms.

In conclusion, our findings contribute to the research on personalized advertising on social networking sites. More specifically, it examined the perceived cost and benefit side of personalization based on the privacy calculus theory. We find initial evidence for the fact that the perceived costs seem to have a stronger effect on the perceptions of personalized advertisements than the perceived benefits. Furthermore, we examined the moderating role of source type. It becomes clear that this helps to explain the fact that previous studies found both positive as well as negative effects of personalization (e.g., De Keyzer et al., 2015; van Doorn & Hoekstra, 2013). It seems to matter in which context personalization occurs, and future endeavors focusing on the implications of and perceptions towards personalization should take that into account.

REFERENCES

Acquisti, A., Brandimarte, L., & Loewenstein, G. (2015). Privacy and human behavior in the age of information. *Science*, *347*(6221), 509–515. https://doi.org/10.2139/ssrn.2580411

Arora, N., Dreze, X., Ghose, A., Hess, J. D., Iyengar, R., Jing, B., Joshi, Y., Kumar, V., Lurie, N., Neslin, S. A., Sajeesh, S., Su, M., Syam, N. B., Thomas, J., & Zhang, Z. J. (2008). Putting one-to-one marketing to work: Personalization, customization, and choice. *Marketing Letters*, *19*(3/4), 305–321.

Atzmüller, C., & Steiner, P. M. (2010). Experimental vignette studies in survey research. *Methodology*, *6*(3), 128–138. https://doi.org/10.1027/1614-2241/a000014

Baek, T. H., & Morimoto, M. (2012). Stay away from me. *Journal of Advertising*, *41*(1), 59–76. https://doi.org/10.2753/JOA0091-3367410105

Barnard, L. (2014). *The cost of creepiness: How online behavioral advertising affects consumer purchase intention [Doctoral thesis, University of North Carolina]*. http://search.proquest.com/docview/1545897557?accountid=51189

Baruh, L., Secinti, E., & Cemalcilar, Z. (2017). Online privacy concerns and privacy management: A meta-analytical review. *Journal of Communication*, *67*(1), 26–53. https://doi.org/10.1111/jcom.12276

Boerman, S. C., & Kruikemeier, S. (2016). Consumer responses to promoted tweets sent by brands and political parties. *Computers in Human Behavior*, *65*, 285–294. https://doi.org/10.1016/j.chb.2016.08.033

Boerman, S. C., Kruikemeier, S., & Zuiderveen Borgesius, F. J. (2017). Online behavioral advertising: A literature review and research agenda. *Journal of Advertising*, *46*(3), 363–376. https://doi.org/10.1080/00913367.2017.1339368

Bol, N., Kruikemeier, S., Boerman, S. C., Strycharz, J., de Vreese, C. H., Dienlin, T., Sax, M., & Helberger, N. (2018). Understanding the effects of personalization as a privacy calculus: Analyzing Self-disclosure across health, news, and commerce contexts. *Journal of Computer-Mediated Communication*, *23*(6), 370–388. https://doi.org/10.1093/jcmc/zmy020

Brehm, J. W. (1966). *A theory of psychological reactance*. Academic Press.

Bright, L. F., & Daugherty, T. (2012). Does customization impact advertising effectiveness? An exploratory study of consumer perceptions of advertising in customized online environments. *Journal of Marketing Communications*, *18*(1), 19–37. https://doi.org/10.1080/13527266.2011.620767

Bucher, T. (2017). The algorithmic imaginary: Exploring the ordinary affects of Facebook algorithms. *Information Communication and Society*, *20*(1), 30–44. https://doi.org/10.1080/1369118X.2016.1154086

Chellappa, R. K., & Sin, R. G. (2005). Personalization versus privacy: An empirical examination of the online consumer's dilemma. *Information Technology and Management*, *6*(2–3), 181–202. https://doi.org/10.1007/s10799-005-5879-y

Culnan, M. J. (1993). "How did they get my name?": An exploratory investigation of consumer attitudes toward secondary information use. *MIS Quarterly*, *September*, 341–364. https://doi.org/10.2307/249775

Culnan, M. J., & Armstrong, P. K. (1999). Information privacy concerns, procedural fairness, and impersonal trust: An empirical investigation. *Organization Science*, *10*(1), 104–115. https://doi.org/10.1287/ORSC.10.1.104

de Groot, J. I. M. (2022). The personalization paradox in Facebook advertising: The mediating effect of relevance on the personalization-brand attitude relationship and the moderating effect of intrusiveness. *Journal of Interactive Advertising*, *22*(1), 57–74. https://doi.org/10.1080/15252019.2022.2032492

De Keyzer, F. (2019). *Brand communication on social networking sites [Doctoral thesis, University of Antwerp]*. University of Antwerp.

De Keyzer, F., Dens, N., & De Pelsmacker, P. (2015). Is this for me? How consumers respond to personalized advertising on social network sites. *Journal of Interactive Advertising*, *15*(2), 124–134. https://doi.org/10.1080/15252019.2015.1082450

De Keyzer, F., Dens, N., & De Pelsmacker, P. (2022). How and when personalized advertising leads to brand attitude, click, and WOM intention. *Journal of Advertising*, *51*(1), 39–56. https://doi.org/10.1080/00913367.2021.1888339

De Pelsmacker, P., Dens, N., & Verberckmoes, S. (2019). How ad congruity and interactivity affect fantasy game players' attitude toward in-game advertising. *Journal of Electronic Commerce Research*, *20*(1), 55–74.

Debevec, K., & Romeo, J. B. (1992). Self-referent processing in perceptions of verbal and visual commercial information. *Journal of Consumer Psychology*, *1*(1), 83–102.

Demmers, J., van Dolen, W. M., & Weltevreden, J. W. J. (2018). Handling consumer messages on social networking sites: customer service or privacy infringement? *International Journal of Electronic Commerce*, *22*(1), 8–35. https://doi.org/10.1080/10864415.2018.1396110

Dienlin, T., & Metzger, M. J. (2016). An extended privacy calculus model for snss: Analyzing self-disclosure and self-withdrawal in a representative U.S. sample. *Journal of Computer-Mediated Communication*, *21*(5), 368–383. https://doi.org/10.1111/jcc4.12163

Dinev, T., & Hart, P. (2006). An extended privacy calculus model for e-commerce transactions. *Information Systems Research*, *17*(1), 61–80. https://doi.org/10.1287/isre.1060.0080

Eisend, M., & Tarrahi, F. (2022). Persuasion knowledge in the marketplace: A meta-analysis. *Journal of Consumer Psychology*, *32*(1), 3–22. https://doi.org/10.1002/JCPY.1258

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.2307/3151312

Friestad, M., & Wright, P. (1994). The persuasion knowledge model: How people cope with persuasion attempts. *Journal of Consumer Research*, *21*(1), 1–31. https://doi.org/10.1086/209380

Geuens, M., & De Pelsmacker, P. (2017). Planning and conducting experimental advertising research and questionnaire design. *Journal of Advertising*, *46*(1), 83–100. https://doi.org/10.1080/00913367.2016.1225233

Gironda, J. T., & Korgaonkar, P. K. (2018). iSpy? Tailored versus invasive ads and consumers' perceptions of personalized advertising. *Electronic Commerce Research and Applications*, *29*(November 2017), 64–77. https://doi.org/10.1016/j.elerap.2018.03.007

Grubbs Hoy, M., & Milne, G. (2010). Gender differences in privacy-related measures for young adult Facebook users. *Journal of Interactive Advertising*, *10*(2), 28–45. https://doi.org/10.1080/15252019.2010.10722168

Hair, J. F. Jr., Black, W., Babin, B. J., & Anderson, R. E. (2014). *Multivariate data analysis* (7th ed.). https://doi.org/10.1007/978-3-319-01517-0_3

Ham, C. (2016). Exploring how consumers cope with online behavioral advertising. *International Journal of Advertising*, *36*(4), 632–658. https://doi.org/10.1080/02650487.2016.1239878

Hawkins, R. P., Kreuter, M., Resnicow, K., Fishbein, M., & Dijkstra, A. (2008). Understanding tailoring in communicating about health. *Health Education Research*, *23*(3), 454–466. https://doi.org/10.1093/her/cyn004

Hayes, J. L., Brinson, N. H., Bott, G. J., & Moeller, C. M. (2021). The influence of consumer–brand relationship on the personalized advertising privacy calculus in social media. *Journal of Interactive Marketing*, *55*, 16–30. https://doi.org/10.1016/J.INTMAR.2021.01.001

Hayes, J. L., King, K. W., & Ramirez, A. (2016). Brands, friends, & viral advertising: A social exchange perspective on the ad referral processes. *Journal of Interactive Marketing*, *36*, 31–45. https://doi.org/10.1016/j.intmar.2016.04.001

Homer, P. M. (1990). The mediating role of attitude toward the ad: Some additional evidence. *Journal of Marketing Research*, *27*(1), 78. https://doi.org/10.2307/3172553

Hsu, C. L., & Lin, J. C. C. (2008). Acceptance of blog usage: The roles of technology acceptance, social influence and knowledge sharing motivation. *Information & Management*, *45*(1), 65-74. https://doi.org/10.1016/j.im.2007.11.001

IHS Markit. (2017). *The economic value of behavioural targeting in digital advertising*. Retrieved from: http://datadrivenadvertising.eu/wp-content/uploads/2017/09/BehaviouralTargeting_FINAL.pdf

Kaspar, K., Weber, S. L., & Wilbers, A.-K. (2019). Personally relevant online advertisements: Effects of demographic targeting on visual attention and brand evaluation. *Plos One*, *14*(2), e0212419. https://doi.org/10.1371/journal.pone.0212419

Kelly, L., Kerr, G., & Drennan, J. (2017). Privacy concerns on social networking sites: A longitudinal study. *Journal of Marketing Management*, *33*(17–18), 1465–1489. https://doi.org/10.1080/0267257X.2017.1400994

Kruikemeier, S., van Noort, G., Vliegenthart, R., & de Vreese, C. H. (2013). Getting closer: The effects of personalized and interactive online political communication. *European Journal of Communication*, *28*(1), 53–66. https://doi.org/10.1177/0267323112464837

Kumar, V., & Gupta, S. (2016). Conceptualizing the evolution and future of advertising. *Journal of Advertising*, *45*(3), 302–317. https://doi.org/10.1080/00913367.2016.1199335

Laufer, R. S., & Wolfe, M. (1977). Privacy as a concept and a social issue: A multidimensional developmental theory. *Journal of Social Issues*, *33*(3), 22–42. https://doi.org/10.1111/J.1540-4560.1977.TB01880.X

Leong, L.-Y., Jaafar, N. I., & Ainin, S. (2018). Understanding Facebook commerce (f-commerce) actual purchase from an artificial neural network perspective. *Journal of Electronic Commerce Research*, *19*(1), 75–103.

Li, C. (2016). When does web-based personalization really work? The distinction between actual personalization and perceived personalization. *Computers in Human Behavior*, *54*, 25–33. https://doi.org/10.1016/j.chb.2015.07.049

Li, H., Sarathy, R., & Xu, H. (2011). The role of affect and cognition on online consumers' decision to disclose personal information to unfamiliar online vendors. *Decision Support Systems*, *51*(3), 434–445. https://doi.org/10.1016/j.dss.2011.01.017

Malheiros, M. (2014). *User behaviour in personal data disclosure [Doctoral thesis, University College Londen]*. University College London.

Malheiros, M., Jennett, C., Patel, S., Brostoff, S., & Sasse, M. (2012). Too close for comfort: A study of the effectiveness and acceptability of rich-media personalized advertising. In *Proceedings of the 2012 ACM annual conference on human factors in computing systems* (pp. 579–588). https://doi.org/10.1145/2207676.2207758

Matz, S. C., Kosinski, M., Nave, G., & Stillwell, D. J. (2017). Psychological targeting as an effective approach to digital mass persuasion. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(48), 12714–12719. https://doi.org/10.1073/pnas.1710966114

McAndrew, F. T., & Koehnke, S. S. (2016). On the nature of creepiness. *New Ideas in Psychology*, *43*, 10–15. https://doi.org/10.1016/j.newideapsych.2016.03.003

Miron, A. M., & Brehm, J. W. (2006). Reactance theory - 40 years later. *Zeitschrift Für Sozialpsychologie*, *37*(1), 9–18. https://doi.org/10.1024/0044-3514.37.1.9

Moe, W. W., & Schweidel, D. a. (2012). Online product opinions: Incidence, evaluation, and evolution. *Marketing Science*, *31*(3), 372–386. https://doi.org/10.1287/mksc.1110.0662

Moeller, J., Trilling, D., Helberger, N., Irion, K., & de Vreese, C. (2016). Shrinking core? Exploring the differential agenda setting power of traditional and personalized news media. *Info*, *18*(6), 26–41. https://doi.org/10.1108/info-05-2016-0020

Nissenbaum, H. (2010). *Privacy in context: Technology, policy, and the integrity of social life*. Stanford University Press.

Niu, X., Wang, X., & Liu, Z. (2021). When I feel invaded, I will avoid it: The effect of advertising invasiveness on consumers' avoidance of social media advertising. *Journal of Retailing and Consumer Services*, *58*, 102320. https://doi.org/10.1016/j.jretconser.2020.102320

Noar, S. M., Benac, C. N., & Harris, M. S. (2007). Does tailoring matter? Meta-analytic review of tailored print health behavior change interventions. *Psychological Bulletin*, *133*(4), 673–693. https://doi.org/10.1037/0033-2909.133.4.673

Noar, S. M., Harrington, N. G., & Aldrich, R. S. (2009). The Role of message tailoring in the development of persuasive health communication messages. *Communication Yearbook*, *33*(1947), 73–133.

Pariser, E. (2012). *The filter bubble: What the internet is hiding from you.* Penguin Press.
Pfiffelmann, J., Dens, N., & Soulez, S. (2020). Personalized advertisements with integration of names and photographs: An eye-tracking experiment. *Journal of Business Research*, *111*, 196–207. https://doi.org/10.1016/j.jbusres.2019.08.017
Pirlott, A. G., & MacKinnon, D. P. (2016). Design approaches to experimental mediation. *Journal of Experimental Social Psychology*, *66*, 29–38. https://doi.org/10.1016/j.jesp.2015.09.012
Schoenberg, N. E., & Ravdal, H. (2000). Using vignettes in awareness and attitudinal research. *International Journal of Social Research Methodology*, *3*(1), 63–74. https://doi.org/10.1080/136455700294932
Schultz, D. (2016). The future of advertising or whatever we're going to call it. *Journal of Advertising*, *45*(3), 276–285. https://doi.org/10.1080/00913367.2016.1185061
Segijn, C. M., & van Ooijen, I. (2022). Differences in consumer knowledge and perceptions of personalized advertising: Comparing online behavioural advertising and synced advertising. *Journal of Marketing Communications*, *28*(2), 207–226. https://doi.org/10.1080/13527266.2020.1857297
Smit, E. G., van Noort, G., & Voorveld, H. a M. (2014). Understanding online behavioural advertising: User knowledge, privacy concerns and online coping behaviour in Europe. *Computers in Human Behavior*, *32*, 15–22. https://doi.org/10.1016/j.chb.2013.11.008
Spears, N., & Singh, S. N. (2004). Measuring attitude toward the brand and purchase intentions. *Journal of Current Issues and Research in Advertising*, *26*(2), 53–66. https://doi.org/10.1080/10641734.2004.10505164
Statista Inc. (2021). *Most popular social media networks worldwide as of July 2021, ranked by number of active users.* Retrieved from: https://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users/
Strycharz, J., van Noort, G., Helberger, N., & Smit, E. (2019). Contrasting perspectives – practitioner's viewpoint on personalised marketing communication. *European Journal of Marketing*. https://doi.org/10.1108/EJM-11-2017-0896
Tam, K. Y., & Ho, S. Y. (2006). Understanding the impact of web personalization on user information processing and decision outcomes. *MIS Quarterly*, *30*(4), 865–890. http://dl.acm.org/citation.cfm?id=2017317.2017322
Thurman, N., Moeller, J., Helberger, N., & Trilling, D. (2018). My Friends, editors, algorithms, and I. *Digital Journalism*, *7*(4), 447–469. https://doi.org/10.1080/21670811.2018.1493936
Ur, B., Leon, P. G., Cranor, L. F., Shay, R., & Wang, Y. (2012). Smart, useful, scary, creepy. In *Proceedings of the eighth symposium on usable privacy and security*. https://doi.org/10.1145/2335356.2335362
van Doorn, J., & Hoekstra, J. C. (2013). Customization of online advertising: The role of intrusiveness. *Marketing Letters*, *24*(4), 339–351. https://doi.org/10.1007/s11002-012-9222-1
Verbeij, T., Pouwels, J. L., Beyens, I., & Valkenburg, P. M. (2021). The accuracy and validity of self-reported social media use measures among adolescents. *Computers in Human Behavior Reports*, *3*, 100090. https://doi.org/10.1016/J.CHBR.2021.100090
Voorveld, H. A. M. (2019). Brand communication in social media: A research agenda. *Journal of Advertising*, *48*(1), 14–26. https://doi.org/10.1080/00913367.2019.1588808
Wallander, L. (2009). 25 years of factorial surveys in sociology: A review. *Social Science Research*, *38*(3), 505–520. https://doi.org/10.1016/j.ssresearch.2009.03.004
Walrave, M., Poels, K., Antheunis, M. L., Van den Broeck, E., & van Noort, G. (2016). Like or dislike? Adolescents' responses to personalized social network site advertising. *Journal of Marketing Communications*, *7266*(May), 1–18. https://doi.org/10.1080/13527266.2016.1182938
Wang, T., Duong, T. D., & Chen, C. C. (2016). Intention to disclose personal information via mobile applications: A privacy calculus perspective. *International Journal of Information Management*, *36*(4), 531–542. https://doi.org/10.1016/j.ijinfomgt.2016.03.003
Weiss, M. G., Ramakrishna, J., & Somma, D. (2006). Health-related stigma: Rethinking concepts and interventions. *Psychology, Health & Medicine*, *11*(3), 277–287. https://doi.org/10.1080/13548500600595053
White, T. B., Zahay, D. L., Thorbjørnsen, H., & Shavitt, S. (2008). Getting too personal: Reactance to highly personalized email solicitations. *Marketing Letters*, *19*(1), 39–50. https://doi.org/10.1007/s11002-007-9027-9
Wirtz, B. W., Göttel, V., & Daiser, P. (2017). Social networks: Usage intensity and effects on personalized advertising. *Journal of Electronic Commerce Research*, *18*(2), 103–123.
Youn, S., & Kim, S. (2019). Understanding ad avoidance on Facebook: Antecedents and outcomes of psychological reactance. *Computers in Human Behavior*, *98*(April 2018), 232–244. https://doi.org/10.1016/j.chb.2019.04.025
Youn, S., & Shin, W. (2019). Teens' responses to Facebook newsfeed advertising: The effects of cognitive appraisal and social influence on privacy concerns and coping strategies. *Telematics and Informatics*, *38*(February), 30–45. https://doi.org/10.1016/j.tele.2019.02.001

Zarouali, B., Poels, K., Ponnet, K., & Walrave, M. (2018). “Everything under control?”: Privacy control salience influences both critical processing and perceived persuasiveness of targeted advertising among adolescents. *Cyberpsychology*, *12*(1). https://doi.org/10.5817/CP2018-1-5

Zhang, B., & Xu, H. (2016). Privacy nudges for mobile applications: Effects on the creepiness emotion and privacy attitudes. In *Proceedings of the 19th ACM conference on computer-supported cooperative work & social computing* (pp. 1674–1688). https://doi.org/10.1145/2818048.2820073

Zuiderveen Borgesius, F. J., Trilling, D., Möller, J., Bodó, B., de Vreese, C. H., & Helberger, N. (2016). Should we worry about filter bubbles ? *Internet Policy Review*, *5*(1), 1–16. https://doi.org/10.14763/2016.1.401

Appendix

Appendix A. Vignettes

	Low	Medium	High
Health website	Imagine you would visit Facebook. There you see an advertisement for a health website like gezondheidsplein.nl or thuisarts.nl based on your friends' page-likes. Your friends' page-likes are used to show the advertisement. Before you continue with the questionnaire, we would like to ask you to imagine this advertisement.	Imagine you would visit Facebook. There you see an advertisement for a health website like gezondheidsplein.nl or thuisarts.nl based on your friends' page-likes and your gender. Your friends' page-likes and your gender are used to show the advertisement. Before you continue with the questionnaire, we would like to ask you to imagine this advertisement.	Imagine you would visit Facebook. There you see an advertisement for a health website like gezondheidsplein.nl or thuisarts.nl, based on your friends' page-likes, your gender, and interests. Your friends' page-likes, your gender, and your interests are used to show the advertisement. Before you continue with the questionnaire, we would like to ask you to imagine this advertisement.
Governmental website	Imagine you would visit Facebook. There you see an advertisement for a governmental website, like belastingdient.nl or douane.nl based on your friends' page-likes. Your friends' page-likes are used to show the advertisement. Before you continue with the questionnaire, we would like to ask you to imagine this advertisement.	Imagine you would visit Facebook. There you see an advertisement for a governmental website, like belastingdienst.nl or douane.nl based on your friends' page-likes and your gender. Your friends' page-likes and your gender are used to show the advertisement. Before you continue with the questionnaire, we would like to ask you to imagine this advertisement.	Imagine you would visit Facebook. There you see an advertisement for a governmental website, like belastingdienst.nl or nu.nl, based on your friends' page-likes, your gender, and your interests. Your friends' page-likes, your gender, and your interests are used to show the advertisement. Before you continue with the questionnaire, we would like to ask you to imagine this advertisement.
Online news website	Imagine you would visit Facebook. There you see an advertisement for an online newspaper, like volkskrant.nl or nu.nl based on your friends' page-likes. Your friends' page-likes are used to show the advertisement. Before you continue with the questionnaire, we would like to ask you to imagine this advertisement.	Imagine you would visit Facebook. There you see an advertisement for an online newspaper, likevolkskrant.nl or nu.nl based on your friends' page-likes and your gender. Your friends' page-likes and your gender are used to show the advertisement. Before you continue with the questionnaire, we would like to ask you to imagine this advertisement.	Imagine you would visit Facebook. There you see an advertisement for an online newspaper, likevolkskrant.nl or nu.nl, based on your friends' page-likes, your gender, and your interests. Your friends' page-likes, your gender, and your interests are used to show the advertisement. Before you continue with the questionnaire, we would like to ask you to imagine this advertisement.
Online store	Imagine you would visit Facebook. There you see an advertisement for an online store, like zalando.nl or bol.com based on your friends' page-likes. Your friends' page-likes are used to show the advertisement. Before you continue with the questionnaire, we would like to ask you to imagine this advertisement.	Imagine you would visit Facebook. There you see an advertisement for an online store, like zalando.nl or bol.com based on your friends' page-likes and your gender. Your friends' page-likes and your gender are used to show the advertisement. Before you continue with the questionnaire, we would like to ask you to imagine this advertisement.	Imagine you would visit Facebook. There you see an advertisement for an online store, like zalando.nl or bol.com, based on your friends' page-likes, your gender, and your interests. Your friends' page-likes, your gender, and you or interests are used to show the advertisement. Before you continue with the questionnaire, we would like to ask you to imagine this advertisement.

Appendix B. Path Coefficients per Source with the Low Level of Personalization as the Reference Category

	Health website		Governmental website		Online newspaper		Commercial website	
	Path coefficient	p-value	Path coefficient	p-value	Path coefficient	p-value	Path coefficient	p-value
Moderate level of personalization → Perceived creepiness of the advertisement	.173	.051	.145	.109	.169	.036	.176	.056
Moderate level of personalization → Perceived relevance of the advertisement	-.169	.050	-.208	.030	.037	.665	-.188	.028
High level of personalization → Perceived creepiness of the advertisement	.287	<.001	.268	.004	.294	.001	.035	.656
High level of personalization → Perceived relevance of the advertisement	-.240	.009	-.085	.374	.152	.104	-.039	.645
Perceived creepiness of the advertisement → Source attitude	-.126	.068	-.277	<.001	-.200	.005	-.209	.043
Perceived relevance of the advertisement → Source attitude	.578	<.001	.603	<.001	.522	<.001	.382	<.001
Number of FB friends → Perceived creepiness of the advertisement	-.055	.418	-.031	.701	-.066	.403	-.048	.524
Number of FB friends → Perceived relevance of the advertisement	-.069	.407	.147	.178	-.021	.830	.110	.099
Number of FB friends → Source attitude	-.114	.110	.059	.322	-.072	.238	.020	.675
Days spent on FB → Perceived creepiness of the advertisement	-.067	.389	.119	.096	.043	.624	-.281	.002
Days spent on FB → Perceived relevance of the advertisement	.022	.814	.036	.647	.114	.149	.295	<.001
Days spent on FB → Source attitude	.026	.684	-.096	.080	.010	.902	-.023	.784

Appendix C. Path Coefficients per Source with the Moderate Level of Personalization as the Reference Category

	Health website		Governmental website		Online newspaper		Commercial website	
	Path coefficient	p-value	Path coefficient	p-value	Path coefficient	p-value	Path coefficient	p-value
Low level of personalization → Perceived creepiness of the advertisement	-.168	.053	-.141	.097	-.162	.040	-.183	.081
Low level of personalization → Perceived relevance of the advertisement	.164	.067	.203	.032	-.035	.663	.196	.032
High level of personalization → Perceived creepiness of the advertisement	.114	.225	.133	.135	.128	.185	-.147	.133
High level of personalization → Perceived relevance of the advertisement	-.071	.433	.109	.219	.116	.216	.155	.073
Perceived creepiness of the advertisement → Source attitude	-.126	.066	-.277	<.001	-.200	.004	-.209	.033
Perceived relevance of the advertisement → Source attitude	.578	<.001	.603	<.001	.522	<.001	.382	<.001
Number of FB friends → Perceived creepiness of the advertisement	-.055	.463	-.031	.715	-.066	.393	-.048	.504
Number of FB friends → Perceived relevance of the advertisement	-.069	.365	.147	.198	-.021	.830	.110	.099
Number of FB friends → Source attitude	-.114	.133	.059	.326	-.072	.258	.020	.665
Days spent on FB → Perceived creepiness of the advertisement	-.067	.389	.119	.119	.043	.631	-.281	.003
Days spent on FB → Perceived relevance of the advertisement	.022	.812	.036	.658	.114	.138	.295	<.001
Days spent on FB → Source attitude	.026	.688	-.096	.074	.010	.899	-.023	.789