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When is personalized advertising crossing personal boundaries? How type of information, data sharing, and personalized pricing influence consumer perceptions of personalized advertising

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ABSTRACT

We examine the boundary conditions of online personalized advertising by investigating when it is perceived as acceptable and when negative feelings predominate. We conducted a 4 (type of information) x 2 (sharing of information) x 3 (personalized pricing) scenario-based experiment among a representative sample of the Dutch population (N = 1244). Results suggest that, in general, people hold quite negative attitudes towards personalized advertising. Furthermore, ads that use individual-specific and private information (i.e., email content and name), when personal information is shared with other parties, and a higher personalized price all led to lower perceptions of personalized advertising and more resistance to the context (the website), message (the ad), and source (the advertiser). In addition, we find a tipping point: ads that present a higher price based on personal information led to even stronger negative perceptions. For advertisers, our findings imply that boundaries can be crossed in personalizing advertising.

Introduction

In the current digital society, personal data are readily available online, because we share data, for instance, when we are browsing websites, when we communicate via social media, and when we search information on search engines (Acquisti, Brandimarte, & Loewenstein, 2015). Algorithms help advertisers to use these data to personalize ads, target individuals, and adjust prices. Targeting different segments with different marketing messages is currently at the core of marketing (Neumann, Tucker, & Whitfield 2019) and personalization is developing in a fast pace. Advertisers can use increasingly sophisticated and distinctive techniques, such as psychographic segmentation, social media analytics, geofencing, IP matching, and practices that 'listen' to what consumers say, listen to, or watch (e.g., keywords and water-marking; Segijn and Van Ooijen, 2020a).

On the one hand, marketers see strong results from ad personalization and continue to invest in it (Everage 2019), and academic research shows that personalized ads can positively influence attention, attitudes, purchases, and click-through rates (e.g., Aguirre, Mahr, Grewal, Ruyter, & Wetzes, 2015; Bang and Wojdynski 2016; Bartsch and Klof 2019; Lambrecht and Tucker 2013; Matz, Kosinski, Nave, & Stillwell, 2017). Studies in which people were asked to give their opinions about online personalized advertising have consistently shown that people do understand that personalized advertising can be useful and may show more personally relevant and informative ads (e.g., McDonald and Cranor 2010; Smit, Noort, & Voorve, 2014; Turow, King, Hoofngle, Bleakley, & Hennessy, 2009; Ur et al., 2012), increase convenience (Segijn and Van Ooijen 2020b), and can result in economic benefits such as more discounts (Segijn and Van Ooijen 2020a; Strycharz et al., 2019), and scholars question the accuracy of digital consumer profiles (Neumann, Tucker, and Whitfield 2019). Additionally, personalized advertising has shown to lead to reactance, ad avoidance, ad blocking, and less trust (e.g., Bleier and Eisenbeiss 2015; Bol et al., 2018; Brinson, Eastin, and Cicchirillo 2018; Ham 2017).

This trade-off between the benefits and risks of personalized advertising is reflected in the ‘personalization paradox’ (Aguirre et al., 2015; Awad and Krishnan 2006). This paradox describes how personalized advertising can be both an effective and an ineffective marketing...
strategy: personalization can increase ad relevance which consequently stimulates click-through, but it can also increase feelings of vulnerability which lowers click-through rates.

Thus, advertisers need to find a balance between the benefits and risks of personalized advertising. Therefore, in this study, we aim to gain insights into which forms of personalized ads are perceived as acceptable and in which situations negative feelings predominate. By doing so, we aim to answer the call for more research to "understand how consumers respond to the usage of various types and amounts of personal data with respect to resistance, acceptance, and [...] advertising outcomes" and "identify the tipping point, including the point where consumers feel that data collection for OBA becomes too invasive, what they consider acceptable or unacceptable" (Boerman, Kruikemeier, and Zuiderveen Borgesius 2017, p. 272). Based on communication privacy management theory (Petronio 2012), information boundary theory (Sutin, Palme, Tan, & Phang, 2013), and social contract theory (Dunfee, Craig Smith, & Ross, 1999), we investigate how people’s perceptions of personalized advertising are affected by (1) the type of personal information that is used to personalize ads, (2) whether or not personal information is shared with other parties, and (3) whether or not the ad uses personalized pricing.

Our study contributes to existing research in several ways. First, our study adds to existing knowledge about people’s perceptions of personalized advertising by explicitly looking for boundary conditions for people’s acceptance of online personalization. By combining three key elements of personalized advertising (type of information, data sharing, and personalized pricing) we seek to find the tipping point, that is what type of personalized advertising is still acceptable. We specifically focus on boundary conditions which have been central to many renowned theoretical models in privacy research (e.g., communication privacy management theory), but have not been systematically tested in many studies. This nuanced and in-depth knowledge is needed to better understand how people respond to the variety of personalization practices (that may occur on a daily basis). Second, to our knowledge, despite its importance, this is the first study to investigate the influence of personalized pricing in the context of personalized advertising. Third, we investigate these questions with a scenario-based experiment among a large representative sample of the Dutch population, which contributes to the generalizability and external validity of our findings.

Types of information used to personalize advertising

Personalized communication is often used to deliver the right message at the right time to the right person in a cost-efficient way (Kim and Huh 2017). Personalized advertising involves incorporating elements in a message that refer to each individual recipient and are based on the recipient’s personal characteristics and information (e.g., Baek and Morimoto 2012; Bang et al., 2019; De Keyzer, Dens, & De Pelsmacker, 2015; Maslowska, Smit, & Putte, 2016). This personal information is mostly collected online. Next to personalizing the content of the message, advertisers can also monitor people’s online behavior and use the collected information to show people individually targeted advertisements. This practice is referred to as targeted advertising or online behavioral advertising (Boerman et al., 2017; Varnali 2019). Both content personalization and targeting involve collecting personal information and using this information in marketing practices. Because we want to be inclusive, we refer to online personalized advertising as all online ads that use personal information to target specific individuals. This can be done either by adapting the message (content personalization) or by exposing only specific people to the message (targeting individuals). The level of personalization of an ad is based on the type of data that is used to target the ad, and the amount of information that is used (Boerman, Kruikemeier, and Zuiderveen Borgesius 2017). Advertisers can use a wide range of types of information, such as demographic data (e.g., name, age, gender), location, online shopping behavior, click-through responses to ads, and communication content (e.g., emails, social media posts; Aguirre et al., 2015; Boerman et al., 2017; Kim & Huh, 2017).

The nature and content of these types of information influence the perception of how private this information is perceived, and thus probably the extent to which people believe it is acceptable when advertisers collect and use this information. Research has shown that people’s perceptions of personalized advertising and its effects vary depending on the type of data that is used to create the ad. Malheiro and et al. (2012) found that people felt less comfortable when an ad was showing a person’s photo, name, or age, compared to when the ad mentioned the holiday destination they were searching for. Furthermore, research has shown that adding personal information (e.g., name, age, transaction information, and/or location) to a targeted ad (based on browsing history) makes it more intrusive (Van Doorn and Hoeksma 2013) and make people feel more vulnerable (Aguirre et al., 2015).

These different responses may be explained by the notion that people do not consider all personal information as equally personal or privacy sensitive (Walrave, Poels, Anheanus, Broeck, & Noort, 2018). We believe that there are two reasons why people perceive some types of information to be less acceptable than others. First, types of information used to personalize and target advertising can be categorized as individual-specific that can identify an individual without additional information (i.e., name, identification number, or facial recognition data), or information that is not individual-specific that can only identify or trace back to you when it is combined with additional information (i.e., online behavior, location, purchases). People’s responses to these types of information may differ because of a difference in psychological ownership (Jussila et al., 2015; Pierce, Kostova, and Dirks 2003). The core of the construct of psychological ownership is people’s sense of possession of an object (‘it’s mine’), where people feel there is a close connection between an object and the self. Moreover, this psychological ownership is not only cognitive (i.e., a person’s awareness, thoughts, and beliefs about the object), but also affective (Jussila et al., 2015; Pierce, 2003). Thus, people can associate meaning and emotions to the target of possession. The feelings of ownership towards an object have strong psychological and behavioral effects, such as the tendency to maintain and protect the object (Pierce et al., 2003). In the context of personalized advertising, we argue that people have a stronger feeling of psychological ownership regarding individual-specific information because they can be directly identified by such information, and thus is truly ‘their information’. As not individual-specific information does not directly identify a person and could also apply to many others, this type of information will cause less feelings of ownership. Therefore, we expect that people will have a greater tendency to protect individual-specific information, and the perceptions of the use of individual-specific information to personalize advertising are likely to be more negative compared to not individual-specific information.

Second, although people do understand that companies collect and use personal information online (McDonald and Cranor 2010; Smit, Noort, & Voorveld, 2014), they may not accept the collection and usage of all types of information. Communication privacy management theory (Petronio 2012) and information boundary theory (Sutin et al., 2013) propose that people create rules or boundaries regarding who is denied or granted access to specific personal information. When information is perceived to be too personal or when they expect information to remain private (i.e., personal communication), advertisers cross such a boundary or rule, which may disturb them making people feel anxious or uncomfortable (Sutin et al., 2013). Therefore, we believe that people’s perceptions of personalized advertising may also be affected by how private people expect specific information to be.

Next to more general perceptions of personalized advertising, the type of information used to personalize online advertising may also directly affect consumers’ behavior to and attitudes toward the message (i.e., the ad itself), the context (i.e., the website), and the source (i.e., the advertiser). When the type of information used to personalize an ad is perceived as too personal and intrusive, this may cause resistance or
reactance (Chen et al., 2019; White et al., 2008). People can resist advertising using several strategies: avoidance, contesting, and empowerment (Fransen, Verlegh, Kirmani, & Smi, 2015). In this study, we focus on the first two strategies. First, we expect people to try to avoid personalized advertising that is crossing a boundary. Avoidance can be done physically (i.e., with strategies aimed at not seeing or hearing the ad) or cognitively (i.e., by not paying attention; Fransen et al., 2015). We propose that people may resist personalized advertising that is deemed to be too personal and intrusive, by avoiding the ad (Morimoto 2020) and the website that is showing the ad. Second, consumers can resist advertising by contesting the source or message (Fransen et al., 2015). Resistance then is manifested by dismissing the source of the ad, which may result in reevaluating one’s personal attitude toward this source in a negative direction. Based on the notion of psychological ownership (Jussila et al., 2015; Pierce et al., 2003), communication privacy management theory (Petronio 2012) and information boundary theory (Sutanto et al., 2013), we therefore propose that the type of information influences four types of responses:

**H1.** Personalized ads that are based on individual-specific and more private personal information (vs. personalized ads that are based on less personal information) lead to more a) negative perceptions of personalized advertising, b) avoidance of the ad, c) avoidance of the website, and d) negative attitudes toward the advertiser.

**Responses to data sharing**

When people are using the internet, they are – wittingly or unwittingly – letting websites collect personal information. This information is then often shared, mostly for marketing purposes, with various third parties through third-party elements and cookies included in the website. Third-party content is present on the majority of websites, especially on news sites. An analysis of 500 popular sites and prominent news sites in seven European countries (Finland, France, Germany, Italy, Poland, Spain, and the UK) showed that 95% of the news websites contain third-party content, and over 90% set at least one third-party cookie (Libert and Nielsen 2018).

Research has shown that people are concerned about their privacy with respect to the level of dissemination of their personal information for secondary uses by affiliates and third-parties, even when the data was shared by trusted retailers (Jai, Burns, & King, 2013). Other studies show that people experience a loss of control over their data, and over who knows about you (Strycharz et al., 2019; Segijn and Van Ooijen 2020a). A notion often referred to as information asymmetry, which is the situation in which an advertiser or data processor holds disproportionately more information about the consumer than she does, creating an imbalance in knowledge and decision-making power (Bol et al., 2020; Helberger, Huh, Milne, Strycharz, & Sundaram, 2020; Mittelstadt et al., 2016).

In addition, perceptions of risk and unfairness are higher when a website shares personal and website navigation data with third-party creating an imbalance in knowledge and decision-making power (Bol et al., 2020; Helberger, Huh, Milne, Strycharz, & Sundaram, 2020; Mittelstadt et al., 2016).

Sharing personal information can even breach an implied ‘social contract’ between the consumer and company (Miyazaki 2008; Kruikemeier, Boerman, and Bol 2020). The social contract, in the context of online communication, is a hypothetical contract that people feel they have when they share their personal information to online businesses (Kruikemeier et al., 2020). Following social contract theory (Dunfee et al., 1999), this contract involves an implied mutual understanding that both parties will make responsible and fair use of personal information. Thus, although people may approve of the collection and use of their personal information by specific, trusted parties, they may believe that sharing this information with other, unknown, parties crosses a boundary. Therefore, we propose:

**H2.** When personal information used to personalize an ad is shared with other parties (vs. not shared), consumers will show more a) negative perceptions of personalized advertising, b) avoidance of the ad, c) avoidance of the website, and d) negative attitudes toward the advertiser.

**Responses to personalized pricing**

Next to personalizing who to target with an ad, advertisers can also use data to personalize the price for their products or services. This so-called personalized pricing can be defined as “differentiating the online price for identical products or services based on information a company has about a potential customer” (Poort & Zuiderveen Borgesius, 2019, p. 2). Although personalized pricing has been around (offline and online) for a long time (e.g., loyalty discounts, status-based discounts), it is rapidly spreading, fueled by technological progress and the vast amount of (personal) data that is now available online (Liu & Greene, 2020, pp. 145–153; Seele et al., 2019). Personal information and online behavior allow advertisers to build consumer profiles and pricing algorithms can estimate consumers’ willingness to pay. Industries that commonly use personalized pricing are transportation, tourism, commerce, and amusement and sports industries (Rekettey and Pryanjić 2020). Examples include personalized pricing of your Uber ride based upon your location and level of your smartphone battery (Dakers 2016), a personal price for products in online shops such as Amazon based upon your previous purchase behavior (Townley, Morrison, and Yeung 2017), and hotel room rates that change based upon your zip code, browser, and device (Mattioni 2012).

Generally, price personalization is allowed by law, as long as the practice does not lead to discrimination on the basis of, for instance, ethnicity (Zuiderveen Borgesius 2020; Zuiderveen Borgesius and Poort 2017). However, the practice of personalized pricing also sparks a normative and legal debate, primarily focusing on unfairness and whether it should be prohibited (Poort & Zuiderveen Borgesius, 2019).

Particularly in the digital environment, personalized pricing can be seen as highly unfair and inappropriate, as online companies, on the one hand, are able to collect large amounts of personal data and can decide to adjust their prices accordingly, whereas consumers, on the other hand, lack transparent insights into the process of personalized pricing (Townley et al., 2017; Yeung 2017). This so-called information asymmetry can make consumers vulnerable to exploitation and leaves an unholy feeling of unfair treatment.

Townley et al. (2017) argue that Nissenbaum’s (2009) concept of contextual integrity can help explain why people feel so strongly about personalized pricing online. As consumers can often only assume that they have been unfairly treated, they may base their price fairness perceptions on expectations they have about appropriate and inappropriate practices regarding their personal data (Townley et al., 2017; Nissenbaum 2009). In the offline business-to-consumer context, prices are offered on a uniform, universal, and transparent basis at each moment in time. Even price differentiation is often transparent, as companies often communicate the discounts they apply openly to the public (e.g., in case of weekly discounts or fixed student discounts). When people go online to buy products, they may apply the same expectations they have about offline shopping to the online business-to-consumer context. If consumers find out – or merely suspect – that the process of pricing is not uniform, universal, and transparent, their expectations might be violated, and the personalized pricing deemed inappropriate.

Research has shown that consumers find such personalized pricing unacceptable (Poort & Zuiderveen Borgesius, 2019). Unfair pricing is expected to lead to lower perceived price value and dissatisfaction,
which may ultimately lead to negative behavioral responses, such as negative word-of-mouth (Xia, Monroe, and Cox 2004). Research has indeed showed that feelings of unfairness can reduce people’s intention to purchase the advertising product, but that people are more likely to purchase, if the price inequality is in their own favor (Richards et al., 2016). Therefore, we expect that acceptance and resistance may also depend on the direction of the personalized price: Where a higher price may evoke feelings of unfairness and resistance, a lower price is also personally beneficial and thus could lead to more positive perceptions and less resistance. Therefore, we propose:

H3. When advertisers increase the price of a product in an ad based on personal information (vs. when the price is lower, or the same for others), consumers will show more a) negative perceptions of personalized advertising, b) avoidance of the ad, c) avoidance of the website, and d) negative attitudes toward the advertiser.

Lastly, we examine how the three factors interact (i.e., type of information, sharing of information, and personalized pricing) and together influence responses to personalized advertising. As we mentioned before, based on the information boundary theory (Sutanto et al., 2013), we expect that the factors might reinforce each other and collectively affect consumers in a stronger way as multiple boundaries may be crossed. For instance, people might be more negative to certain types of information, such as email content, as this type of data might be highly personal to certain people. However, people might be more positive towards the use of this very personal data if the company who collects the data is not sharing it with others. But, if a company shares the information with others, a boundary is crossed. As a consequence, people might be particularly negative if such a combination of practices occurs. However, it might also work the other way around. If a company uses the email content of a consumer, but the consumer receives a lower price offer because of it, consumers might be more positive towards the use of highly personal data. Yet, research on the combination of these aspects is largely absent in the literature, which makes the development of specific expectations difficult. For that reason, we propose to develop the following research question:

RQ1: How do the factors of personalized advertising (i.e., type of information, sharing of information, and personalized pricing) interact and affect consumers’ a) perceptions of personalized advertising, b) avoidance of the ad, c) avoidance of the website, and d) attitudes toward the advertiser.

Method

Design

We used a 4 (type of information: name vs. content of sent and received emails vs. previously visited websites vs. products clicked on or viewed in a web shop) × 2 (sharing of information: shared with others vs. not shared) × 3 (personalized pricing: price higher vs. price lower vs. price the same compared to others) between subjects design. This design resulted in a total of 24 scenarios. All respondents were presented two different scenarios, making it a mixed design: variables were both manipulated between subjects (type of information, sharing of information, and personalized pricing) and within subjects (order of assigned scenarios).

Pre-test

To find types of information that varied regarding how comfortable people felt about the collection and use of this personal information, we conducted a pre-test. In this pre-test, we presented a convenience sample of 18 respondents 13 brief scenarios (“Imagine that you are visiting a website. On that website there is an ad based on [type of information].”) to compare 13 types of information that differed in how individual-specific they were (e.g., name, gender, age, location, online purchases, videos watched). We then asked participants to indicate with seven-point semantic differentials to what extent they thought this scenario was unacceptable – acceptable and creepy – not creepy. Table 1 shows the outcomes of this pre-test. The information types chosen for the experiment represented the two types of information that people felt most comfortable with (i.e., products one clicked on and viewed in a web shop, and websites one visited before) and the two that they felt least comfortable with (i.e., name and email content). In line with our reasoning, these types of information differed with regard to whether they are individual-specific, and whether people expect to this information to be used for personalized advertising or remain private.

Participants and procedure

An online research company invited 1523 to participate in an online survey, of which 1244 completed the questionnaire in May 2016. This was based on representative sample of the Dutch population, and was aged, on average, 54 years old (range 18–89, SD = 16.85), 51.7% were female, and were almost equally distributed across educational levels (lower level: 32.4%; middle level: 33.2%; higher level: 34.5%). When participants entered the online survey, they were exposed to a random selection of two out of 24 scenarios. The scenarios read:

Try to imagine the following situation as vividly as possible:

Imagine that you are visiting a website. On this website, there is an advertisement for a product that is based on [type of information].

This personal information is used to show you the advertisement, and this information is [not available / also available] for other advertisers and companies.

In addition, the price of the product in the advertisement based on your personal information is for you, compared to others, [higher / lower / the same].

After reading one scenario, participants filled out questions on the perceived acceptability and creepiness of the scenario, and their behavioral responses. This was then repeated for a second scenario.

Measures

People’s perceptions of personalized advertising were assessed by asking participants: “To what extent do you find this situation …?” followed by 7-point semantic differentials stating: unacceptable/acceptable; scary/not scary; useless/useful; annoying/not annoying; unpleasant/pleasant; unfair/fair; and shocking/not shocking. The

| Table 1 | Outcomes of pre-test: acceptance and creepiness of various types of information. |
|---------|--------------------------------------------------------------------------------|
| Content of sent and received emails | 1.50*** (1.75) | 1.78*** (1.79) |
| Messages on Facebook | 2.11*** (2.44) | 2.44*** (2.44) |
| Name | 2.39*** (3.17) | 3.17 (3.17) |
| Likes on Facebook | 2.56*** (3.61) | 3.61 (3.61) |
| Location | 2.83* (2.92) | 2.92 (2.92) |
| Online purchases (products, tickets, services, etc.) | 3.11* (3.56) | 3.56 (3.56) |
| News items you read | 2.89** (3.78) | 3.78 (3.78) |
| Search behavior in search engines such as Google | 3.11** (3.94) | 3.94 (3.94) |
| Gender | 3.28 (4.00) | 4.00 (4.00) |
| Age | 3.56 (4.06) | 4.06 (4.06) |
| Videos you watched (for instance on YouTube) | 3.17* (4.28) | 4.28 (4.28) |
| Website you visited | 4.06 (4.56) | 4.56 (4.56) |
| Products you clicked on or viewed in a web shop | 4.06 (4.72) | 4.72 (4.72) |
| Mean | 2.97 (3.60) | 3.60 (3.60) |

Note. One-sample t-tests with the neutral middle point (4) of the scale as a reference point. Types of information chosen for main study are bold. N = 18. ***p < .001, **p < .01, *p < .05.
measure of perceptions consisted of the mean score of the seven items (scenario 1: eigenvalue = 4.57, explained variance = 65.31%; alpha = .91; M = 5.61, SD = 1.31; scenario 2 eigenvalue = 5.13, explained variance = 73.32%; alpha = .94; M = 5.40, SD = 1.46). High scores represent positive perceptions.

Avoidance of the ad was measured on a 7-point scale (1 = totally disagree, 7 = totally agree) with the statements: “I would click on the advertisement” and “I would ignore the advertisement”. These behaviors represent physical avoidance and cognitive avoidance (Fransen et al., 2015). The first statement was recoded, so that the mean of the two items indicate more resistance to the ad (scenario 1: Spearman Brown = .60, M = 5.45, SD = 1.59; scenario 2: Spearman Brown = .54, M = 5.31, SD = 1.60).

To measure avoidance of the website, we asked participants to indicate on a 7-point scale (1 = totally disagree, 7 = totally agree) the extent to which they agreed or disagreed with the statements: “I would revisit the website described in the scenario” and “I would use another website”. Both statements represent physical avoidance of the website (Fransen et al., 2015). The first statement was recoded so that the mean of the two items indicate more resistance to the website (scenario 1: Spearman Brown = .49, M = 4.81, SD = 1.50; scenario 2: Spearman Brown = .62, M = 4.96, SD = 1.63).

People’s attitude change toward the advertiser was assessed on a 7-point scale (1 = totally disagree, 7 = totally agree) with one statement: “My opinion about the advertiser would become more positive”. This statement was recoded so that high scores represent more resistance to the advertiser, with attitudes becoming more negative (scenario 1: M = 5.74, SD = 1.47; scenario 2: M = 5.73, SD = 1.50).

Furthermore, because gender, age, and education has shown to influence people’s responses to online personalized advertising (e.g., Boerman et al., 2017; Sheehan 1999), we asked participants to fill out their gender (1 = male, 2 = female), age (in years), and education to be able to control for their effects.

Results

Descriptive statistics of key variables

As the sample is large and representative, the descriptive statistics provide some useful insights. The descriptive statistics reveal that consumers’ perceptions of personalized advertising were quite low (on average 2.58 on a 7 point-scale), and 84% of the participants scored below the neutral point (4) of the scale.

When looking at the average percentage of scores 5 or higher in scenario 1 and 2, the self-reported resistance is also quite high: 60.6% of the respondents said to avoid personalized ads, and 48.4% said to avoid websites that show the described personalized ads. Additionally, 73.8% reported to negative change their attitude toward an advertiser based on the personalized advertisements in the scenarios. This indicates that – in general – people do not seem to appreciate personalized advertising, and say to resist its message, context, and source. For additional information, the means for each condition are available in Table 6, 7 and 8 in the Online Appendix.

### Table 2
Summary of a multi-level regression model that predicts perceptions towards personalized advertising.

|                      | Model 1 | Model 2 | Model 3 | Model 4 |
|----------------------|---------|---------|---------|---------|
|                      | B (SE)  | B (SE)  | B (SE)  | B (SE)  |
| **Constant**         | 4.52 (.20)*** | 4.52 (.20)*** | 4.52 (.21)*** | 4.67 (.21)*** |
| **Main effects:**    |         |         |         |         |
| Type of information (ref. = products seen) |         |         |         |         |
| Email content        | – .71 (.06)*** | – .71 (.06)*** | – .75 (.09)*** | – .94 (.11)*** |
| Name                 | – .66 (.06)*** | – .66 (.06)*** | – .64 (.09)*** | – .96 (.11)*** |
| Websites visited     | – .16 (.06)*** | – .16 (.06)*** | – .15 (.09)*** | – .34 (.11)*** |
| Sharing (ref. = no sharing) | – .28 (.04)*** | – .31 (.08)*** | – .29 (.09)*** | – .28 (.04)*** |
| Personalized pricing (ref. = no difference) |         |         |         |         |
| Lower price          | – .01 (.05) | – .01 (.05) | – .01 (.05) | – .25 (.11)** |
| Higher price         | – .60 (.05)*** | – .70 (.08)*** | – .60 (.05)*** | – .87 (.10)*** |
| **Interaction effects:** |         |         |         |         |
| Personalized pricing and sharing (ref. = no difference*no sharing) |         |         |         |         |
| Lower prices*Sharing  | –         | – .09 (.11) | –         | –         |
| Higher prices*Sharing | –         | – .20 (.11)** | –         | –         |
| Sharing and type of information (ref. = no sharing*products seen) |         |         |         |         |
| Sharing*Email        | –         | –         | .09 (.12) | –         |
| Sharing*Name         | –         | –         | – .04 (.12) | –         |
| Sharing*Websites visited | –         | –         | – .02 (.12) | –         |
| Personalized pricing and type of information (ref. = no difference*products seen) |         |         |         |         |
| Lower price*Email    | –         | –         | –         | – .23 (.15) |
| Lower price*Name     | –         | –         | –         | .42 (.15)*** |
| Lower price*Websites visited | –         | –         | –         | .33 (.15)** |
| Higher price*Email   | –         | –         | –         | .46 (.15)*** |
| Higher price*Name    | –         | –         | –         | .50 (.15)** |
| Higher price*Websites visited | –         | –         | –         | .17 (.15) |
| **Control variables:** |         |         |         |         |
| Female               | – .28 (.06)*** | – .28 (.06)*** | – .28 (.06)*** | – .28 (.06)*** |
| Age                  | – .01 (.00)*** | – .01 (.00)*** | – .01 (.00)*** | – .01 (.00)*** |
| Educational level    | .01 (.02)   | .02 (.02)   | .01 (.02)   | .02 (.02)   |
| Order                | – .05 (.04) | – .05 (.04) | – .05 (.04) | – .05 (.04) |
| **Observations**     | 2484      | 2484      | 2484      | 2484      |
| **Residuals**        | 1242      | 1242      | 1242      | 1242      |
| Log Likelihood       | – 3970.71  | – 3967.08  | – 3970.05  | – 3960.82  |
| AIC                  | 7967.42    | 7964.16    | 7972.11    | 7959.64    |
| BIC                  | 8043.05    | 8051.43    | 8065.19    | 8070.17    |

Note. B = b-coefficient; SE = Standard Error; *p < .10, **p < .05, ***p < .01, ****p < .001.
The conditions did not significantly differ with regard to education (type of information scenario 1 $\chi^2 (6) = 11.29, p = .080$, scenario 2 $\chi^2 (6) = 8.13, p = .229$; data sharing scenario 1 $\chi^2 (2) = 0.22, p = .897$, scenario 2 $\chi^2 (2) = 5.84, p = .054$; personalized pricing scenario 1 $\chi^2 (4) = 3.56, p = .469$, scenario 2 $\chi^2 (4) = 1.67, p = .796$) and gender (type of information scenario 1 $\chi^2 (3) = 4.72, p = .193$, scenario 2 $\chi^2 (3) = 1.48, p = .687$; data sharing scenario 1 $\chi^2 (1) = 1.97, p = .161$, scenario 2 $\chi^2 (1) = 3.10, p = .078$; personalized pricing scenario 1 $\chi^2 (2) = 0.04, p = .979$, scenario 2 $\chi^2 (2) = 1.84, p = .399$). We found one significant difference for age (type of information scenario 1 $F(3, 1237) = 1.04, p = .372$, scenario 2 $F(3, 1237) = 0.49, p = .691$; data sharing scenario 1 $F(1, 1237) = 2.71, p = .100$, scenario 2 $F(1, 1237) = 3.88, p = .049$; personalized pricing scenario 1 $F(2, 1237) = 0.55, p = .577$, scenario 2 $F(2, 1237) = 0.07, p = .933$). This means that the randomization between conditions was mostly successful, and random noise caused by potential individual-related differences between conditions was minimal. To ensure that minor differences between the conditions did not confound our effects, we did include all demographic variables as covariates in all analyses.

### Hypothesis testing – statistical analysis

Because we used a mixed design – respondents were exposed to two scenarios each (making the individual observations nested in respondents) – we used a multilevel regression analysis (using STATA version 15.1). In the multilevel model, we tested the effects of type of information, sharing of information, and personalized pricing, while controlling for spillover effects (repeated exposure), as well as for age, gender, and educational level. Subsequently, we tested the hypotheses. The hypotheses predict a main effect of our three independent variables ‘type of information’, ‘sharing of information’, and ‘personalized pricing’, as well as interaction effects on our four dependent variables, we created a Table for each of the dependent variables separately (see Table 2-5). The main effects are explained in Model 1. The interaction effects are incorporated in Model 2 to 4.

### Effect of type of information

H1 predicted that personalized ads that are based on individual-specific and more private personal information lead to more a) negative perceptions of personalized advertising, b) avoidance of the ad, c) avoidance of the website, and d) negative attitudes toward the advertiser compared to personalized ads that are based on less personal information. With regard to H1a, we found that ads that were based on individual-specific and private information (i.e., email content and name) led to more negative perceptions of personalized advertising ($b_{\text{email content}} = -0.71, p < .001; b_{\text{name}} = -0.66, p < .001$; see Table 2, Model 1) compared to less personal information, such as products one clicked on or viewed in a web shop. Interestingly, the websites visited ($b_{\text{websites visited}} = -0.16, p = .009$) also led to more
negative perceptions compared to products clicked on or viewed in a web shop. Overall, these results support H1a.

We also found support for an effect of the type of information on resistance, confirming H1b, H1c and H1d. Ads that were based on more individual-specific and private information (i.e., email content and resistance, confirming H1b, H1c and H1d. Ads that were based on more individual-specific and private information such as email content and

Overall, these results indicate that people perceive the use of more personalized pricing and type of information (ref. = less personal information, such as the products one has clicked on and viewer in a web shop. Overall, these findings indicate that people perceive the use of more individual-specific and private information such as email content and name as more negative than the use of less personal information.

Effect of data sharing

H2 expected that when personal information used to personalized an ad is shared with other parties, consumers will show more a) negative perceptions of personalized advertising, b) avoidance of the ad, c) avoidance of the website, and d) negative attitudes toward the advertiser, compared to when personal information is not shared. We observed that sharing personal data (vs. not) significantly led to more negative perceptions ($b_{sharing} = -0.28$, $p < .001$, see Table 4, Model 1) and negative attitudes towards the advertiser ($b_{sharing} = 0.20$, $p < .001$, see Table 5, Model 1). We thus found support for H2a-d: Sharing personal information with third parties leads to lower perceptions of personalized advertising and the advertiser and leads to avoidance of the website and ad.

Effects of personalized pricing

H3 proposed that when advertisers increase the price of a product in an ad based on personal information, consumers will show more a) negative perceptions of personalized advertising, b) avoidance of the ad, c) avoidance of the website, and d) negative attitudes toward the advertiser, compared to when the price is lower, or the same for others. We observed that when the price is higher (vs. the same for others), this led to more negative perceptions of personalized advertising ($b_{higher \ price} = -0.60$, $p < .001$, see Table 2, Model 1). In addition, a higher price led to more avoidance of the ad ($b_{higher \ price} = 0.30$, $p < .001$, see Table 3, Model 1), more avoidance of the website ($b_{higher \ price} = 0.73$, $p < .001$, see Table 4, Model 1), and more negative attitudes towards the advertiser ($b_{higher \ price} = 0.44$, $p < .001$, see Table 5, Model 1). We thus found support for H3a-d.

Interestingly, offering a lower price (vs. the same for others) did not influence perceptions of personalized advertising ($b_{lower \ price} = -0.01$, $p = .857$, see Table 2, Model 1) and avoidance of the website ($b_{lower \ price} = 0.03$, $p = .657$, see Table 4, Model 1). Lower prices (vs. the same for others) did significantly lead to less avoidance of the ad ($b_{lower \ price} = -0.15$, $p = .024$, see Table 5, Model 1) and less negative attitudes towards

| Table 4 | Summary of a multi-level regression model that predicts avoidance of the website. |
|---------|----------------------------------------------------------------------------------|
|         | Model 1                          | Model 2                          | Model 3                          | Model 4                          |
|         | B (SE)                           | B (SE)                           | B (SE)                           | B (SE)                           |
| Constant| 3.00 (.23)***                    | 3.01 (.23)***                    | 2.92 (.23)***                    | 2.80 (.24)***                    |
| Main effects: |                                      |                                  |                                  |                                  |
| Type of information (ref. = products seen) |                                  |                                  |                                  |                                  |
| Email   | .71 (.07)***                     | .71 (.07)***                     | .84 (.11)***                     | .97 (.13)***                     |
| Name    | .71 (.08)***                     | .71 (.08)***                     | .78 (.11)***                     | 1.21 (.13)***                    |
| Websites visited |                                  |                                  |                                  |                                  |
| Sharing (ref. = no sharing) |                                  |                                  |                                  |                                  |
| Sharing | .13 (.08)*                       | .13 (.08)*                       | -.21 (.11)*                      | -.34 (.13)**                     |
| Personalized pricing (ref. = no difference) |                                  |                                  |                                  |                                  |
| Lower price | .03 (.07)                       | -.02 (.10)                       | .03 (.07)                        | .27 (.13)                        |
| Higher price | .73 (.07)***                    | .76 (.10)***                     | .73 (.07)***                     | 1.20 (.13)***                    |
| Interaction effects: |                                      |                                  |                                  |                                  |
| Personalized pricing and sharing (ref. = no difference/no sharing) |                                  |                                  |                                  |                                  |
| Lower price*Sharing |                                  |                                  |                                  |                                  |
| Higher price*Sharing |                                  |                                  |                                  |                                  |
| Sharing and type of information (ref. = no sharing/products seen) |                                  |                                  |                                  |                                  |
| Sharing*Email |                                  |                                  |                                  |                                  |
| Sharing*Name |                                  |                                  |                                  |                                  |
| Sharing*Websites visited |                                  |                                  |                                  |                                  |
| Personalized pricing and type of information (ref. = no difference/Products seen) |                                  |                                  |                                  |                                  |
| Lower price*Email |                                  |                                  |                                  |                                  |
| Lower price*Name |                                  |                                  |                                  |                                  |
| Lower price*Websites visited |                                  |                                  |                                  |                                  |
| Higher price*Email |                                  |                                  |                                  |                                  |
| Higher price*Name |                                  |                                  |                                  |                                  |
| Higher price*Websites visited |                                  |                                  |                                  |                                  |
| Control variables |                                      |                                  |                                  |                                  |
| Female  | .24 (.07)**                      | .24 (.07)**                      | .25 (.07)**                      | .23 (.07)**                      |
| Age     | .00 (.00)***                     | .00 (.00)***                     | .01 (.00)***                     | .00 (.00)***                     |
| Educational level | .02 (.02)                      | .02 (.02)                       | .02 (.02)                        | .02 (.02)                        |
| Order   | .14 (.05)**                      | .14 (.05)**                      | .14 (.05)**                      | .13 (.05)**                      |
| NObservations | 4379.13                      | 4379.13                     | 4379.13                        | 4379.13                         |
| NRespondents | 2484                        | 2484                          | 2484                           | 2484                             |
| Log Likelihood | -4.64 (.18)                  | -4.64 (.18)                     | -4.64 (.18)                     | -4.64 (.18)                     |
| AIC     | 8967.85                         | 8967.85                         | 8967.85                         | 8967.85                         |

Note. B = b-coefficient; SE = Standard Error; $^a p < .10$, $^b p < .05$, $^* p < .01$, $^^* p < .001$. 

Effects of data sharing

H2 expected that when personal information used to personalized an ad is shared with other parties, consumers will show more a) negative perceptions of personalized advertising, b) avoidance of the ad, and c) avoidance of the website, and d) negative attitudes toward the advertiser, compared to when personal information is not shared. We observed that sharing personal data (vs. not) significantly led to more negative perceptions ($b_{sharing} = -0.28$, $p < .001$, see Table 2, Model 1). In addition, data sharing led to more avoidance of the ad ($b_{sharing} = 0.16$, $p = .004$, see Table 3, Model 1), avoidance of the website ($b_{sharing} = 0.29$, $p < .001$, see Table 4, Model 1) and negative attitudes towards the advertiser ($b_{sharing} = 0.20$, $p < .001$, see Table 5, Model 1). We thus found support for H2a-d: Sharing personal information with third parties leads to lower perceptions of personalized advertising and the advertiser and leads to avoidance of the website and ad.
the advertiser (b_lower_price = −0.14, p = .023, see Table 4, Model 1). Thus, lower prices (versus no difference in pricing for others) do influence direct responses to the ad and advertiser, but do not influence general perceptions of personalized advertising and the website that shows the ad.

### Interaction effects

To answer our research question, we examined how the three factors (i.e., type of information, sharing of information, and personalized pricing) interact and together influence our dependent variables. The results are included in Table 2–4 in Model 2–4. We tested for all possible two-way interaction effects. For reasons of clarity, we only discuss the significant interaction effects.

We found a significant interaction effect between type of information and personalized pricing on perceptions of personalized advertising (see Table 2, Model 4), ad avoidance (see Table 3, model 4), avoidance of the website (see Table 4, Model 4), and negative attitudes towards the advertiser (see Table 5, Model 4). For ease of interpretation, we visualized the interaction effects in Figs. 1–4. Overall, these figures show that personalized pricing is an important factor: When the price is higher and thus disadvantages the consumer, this is perceived as very negative and this overrules the effect of the type of information. Figs. 1–4 show that the type of information has an influence on general perceptions and resistance when the price in an ad is lower or the same as other people. However, when the price is higher and thus disadvantages the consumer, this decreases the perceptions of personalized advertising and leads to stronger ad avoidance, avoidance of the website, and increased negative attitude towards the advertiser, regardless of the type of information.

### Conclusion and discussion

This study examined the boundary conditions of online personalized advertising by investigating when it is perceived as acceptable and when negative feelings predominate. In particular, we studied peoples’ perceptions of personalized advertising by giving people different scenarios of personalization strategies. We focused on the perceptions of people regarding the type of personal information, data sharing, and personalized pricing. Based on communication privacy management theory (Petronio 2012) and information boundary theory (Sutanto et al., 2013), we expected that personalizing advertisements based on one or more of these elements would be perceived as crossing one or more boundaries. In general, regardless of the way in which advertisements are being personalized, our results suggest that people do not seem to appreciate personalized advertising, and report to resist its message (i.e., avoidance of the ad), context (i.e., avoidance of the website), and source (i.e., negative attitudes toward the advertiser).

The first major finding of our scenario-based experiment is that personalized based on different types of information, data sharing, and personalized pricing all contribute to crossing boundaries of what people deem acceptable advertising practices. As expected, scenarios in
which ads used less individual-specific and private information (i.e., previously visited websites and products one clicked on or viewer in a web shop) were perceived to be more acceptable than scenarios in which ads used more individual-specific and private information (i.e., name and email content). Furthermore, people do not appreciate and show resistance to the website, ad, and advertiser when the collected and used personal information is described to be shared with other parties.

With regard to personalized pricing, some interesting patterns emerged. Our study demonstrates that people hold rather negative perceptions when they are being told to have received a higher price compared to a lower price or no difference in pricing. This is of course very understandable. Yet, when being told that an ad gives a consumer a lower price, this benefit does positively influence direct responses to the ad and advertiser, but does not influence general perceptions of personalized advertising and the website that shows the ad. It seems that not the economic advantage prevails in people’s judgement, but rather the feeling of unfairness due to untransparent practices (Townley et al., 2017).

Our second major finding is that personalized pricing appears to play a prominent role in explaining the negative responses to personalized advertising. Our results indicate that a higher personal price can be the tipping point that makes people no longer accept personalized advertising and resist it. When consumers know that prices are adjusted, they seem to respond very negatively to that across the board. The clear difference in consumer responses to the use of more versus less individual-specific and private types of information in personalized advertising disappears when people were told they would receive a higher price than others would. In other words, receiving a higher price (compared to a lower or same price) seems to overrule the effects of the type of information on one’s reaction to the ad, advertiser, and website.

Interestingly, our scenario-based experiment does not reveal a positive tipping point. Using a type of information that people do not perceive as too private (i.e., previously visited websites or previously viewed products), not sharing the personal data with other parties, and even a lower price, do not seem to positively influence people’s perceptions. They also do not benefit the website, advertiser, or ad. As our study suggests that people in general dislike personalized advertising, making personalized advertisements less creepy does not seem to positively contribute to more positive perceptions regarding ads, advertisers, and websites that advertise such ads. It could be that these seemingly positive conditions of personalized advertising do not outweigh the perceived risks. As described in the ‘personalization paradox’ (Aguirre et al., 2015; Awad and Krishnan 2006), the mere collection of one’s personal data, followed by feelings of vulnerability and unfairness, may not weigh up to the perceived benefits of personalized ads, such as

![Fig. 1. Visualization of interaction effect personalized pricing and type of information on perceptions of personalized advertising in Table 2, Model 4.](image1)

![Fig. 2. Visualization of interaction effect personalized pricing and type of information on ad avoidance in Table 3, Model 4.](image2)

![Fig. 3. Visualization of interaction effect personalized pricing and type of information on avoidance of the website in Table 4, Model 4.](image3)

![Fig. 4. Visualization of interaction effect personalized pricing and type of information on negative attitudes towards the advertiser in Table 5, Model 4.](image4)
economic discounts, receiving more personally relevant offers, and optimizing the shopping experience. Moreover, making people explicitly aware of what can be done with one’s personal data might make people more aware of the negative consequences of personalized advertising, which might imply that personalization can also backfire (Bol et al., 2018).

Theoretical implications

Our study supports the notion that boundary conditions exist when examining the acceptance of online personalization, confirming theoretical notions from psychological ownership (Pierce et al., 2003), communication privacy management theory (Petronio, 2012), and information boundary theory (Sutanto et al., 2013). These findings give us more nuanced understanding of when consumers perceive personalized advertising as less or more acceptable. Furthermore, the interaction effects indicate that the boundary conditions seem to work together and cause a tipping point. Situations in which personalizing a price to the consumers’ disadvantage is perceived as exceptionally unacceptable and causes resistance.

With respect to the type of information, we consistently found different responses to the use of an individual’s email content and name—which are more individual-specific and expected to remain private—versus the use of products one clicked on in web shops and websites one visited before. Thus, our findings confirm our idea that the acceptability of different types of information may be due to whether the information is individual-specific and whether consumers expect this type of information to be used in personalized advertising or remain private. Further research could thus use these two constructs to specify how and hypothesize why the effects of different types of information may differ.

Furthermore, our finding that data sharing reduces perceptions of and increases resistance to personalized advertising, is in line with the idea that sharing personal information breaches an ‘social contract’ between the consumer and company (Kruikemeier et al., 2020; Miyazaki 2008). People are more likely to share personal information if they feel they have an agreement with the online business or website. People share information because the website keeps the personal data safe. Yet, when this ‘contract’ is violated because the information is shared—and a boundary is crossed—people seem to be less inclined to react positively towards personalized advertising.

Finally, our study suggests that personalized pricing is deemed to be unacceptable, even when it is to the benefit of the receiver, proving the importance of the idea of contextual integrity (Townley et al., 2017; Nissenbaum 2009) and providing new evidence for the idea that people find online personalized pricing inappropriate and unfair (Poort & Zuiderveen Borgesius, 2019).

Practical implications

For advertisers, our findings suggest that people do not appreciate personalized advertising in general, and more importantly there is a tipping point: they can go too far in their personalization. When being told that an ad includes a personalized price, especially to the disadvantage of the receiver, people say to not appreciate this and to resist the source, message, and sender in such cases. A direct benefit, by offering a lower personalized price, does reduce avoidance of the ad and diminish the resistance to the advertiser, but may not take away any negative feelings regarding personalized pricing in general. In addition, based on our findings, advertisers could potentially mitigate the negative responses to personalized advertising by refraining from using individual-specific and private information to personalize ads, and by refraining from sharing any collected and used personal information.

For legal scholars, there are at least two important venues to explore. The first one pertains to the question how we should regulate the practices related to personalized advertising. Most practices such as using personal data and personalizing prices are not inherently bad or prohibited. It is the obscure, opaque way in which online companies communicate about their personalization practices that forms the legal debate here. This suggests that we should not only take into account data protection law (e.g., General Data Protection Regulation [GDPR] in EU) to protect the disclosure of people’s personal information, but also unfair commercial practice law (Van Eijk, Hoofnagle, & Kanekens, 2017) as personalized advertising touches the area of (unfair) business-to-consumer fair trade. As personalized advertising might be able to trick the consumer into making an online purchase she otherwise would not have made—for example, by means of displaying or omitting certain information,—this could be considered an unfair practice (Van Eijk et al., 2017).

Second, this study could initiate a discussion about unfair algorithmic targeting. As personalized advertising becomes increasingly more data-driven on an increasingly more sophisticated level, we should not only worry about the impact of and perceptions towards personalized advertising at the individual level, but also at the societal level. People seem to resist data sharing between companies, which is in line with previous work showing that people worry about the loss of control over their data (Acquisti et al., 2015; Seguin and Van Ooijen 2020; Strycharz et al., 2019), and the notion that information asymmetry creates a power imbalance between advertisers and consumers (e.g., Bol et al., 2020; Helberger et al., 2020). In addition, using people’s personal data may not only reinforce existing vulnerabilities, for example those that are less digitally savvy might benefit less from personalized advertising as they are less able to outsmart online companies that might price discriminate against them (Townley et al., 2017), but may also create new ones (Bol et al., 2020). As online companies tend to hold disproportionally more information about the consumer than she does, any group that engages in online activities could be vulnerable to being exploited in unforeseeable ways, which need to be detected, explored, and regulated in the near future.

Limitations

Although scenario-based experimental designs offer the precise experimental control over the manipulation of personalization, and therefore high internal validity, they pose limitations in terms of ecological validity (Bol et al., 2018). Being asked to imagine a situation is very different from actually encountering personalized advertising when browsing websites on a regular day. However, with more ecologically valid research designs, where participants are exposed to a website with different advertisements, it would have been more difficult to ensure exposure and assess its effects. Moreover, scenario-based experiments are commonly used in the domain of online personalized communication (e.g., Aguirre et al., 2015; Bleier and Eisenbeiss 2015; Bol et al., 2018; Van Doorn and Hoekstra 2013). Yet, to validate our findings and further investigate people’s perceptions and responses to other personalization factors, we need more research that utilizes actual personalized advertisements, preferably in people’s own online environment.

Relatedly, our manipulations are often not visible or even purposefully hidden in real life and would have been difficult to simulate in an ecologically valid environment. Take, for example, the manipulation of personalized pricing. In the scenario, we were able to explain to people that the price they received was either higher, lower, or the same. However, in real life, it is very hard—if not impossible—for consumers to tell whether a price is adjusted to their personal data. As personalized pricing is typically not a transparent practice in the digital environment (Townley et al., 2017), people can merely assume, based on their knowledge of personalized practices, that personalization might have occurred. As we made people aware of personalized pricing in the scenarios, this could have affected our findings and their generalizability: people may have been more negative towards personalized pricing and our data might overestimate the negative impact of personalization simply because we made them aware of it. Moreover, when people
become more ‘savvy’ about the practices and possibilities of personalization practices online, it could be that the effect may fade over time. Furthermore, our scenarios asked people to give their opinions about particular elements of personalized advertising. More research is needed to gain insights into how the effects of these elements are moderated by ad-specific factors and individual characteristics, such as the advertising brand. The parties data is shared with (Jai et al., 2015), the actual persuasive message, congruence between website and ad (Goldfarb and Tucker 2011), perceived personalization (De Keyzer et al., 2015), privacy concerns and desire for privacy (Baek and Morimoto 2012; Miyazaki 2008), and personal persuasion knowledge (Ham and Nelson 2016).

Nonetheless, the scenarios do provide insights into how people do respond to different personalization practices. Because the GDPR obligates companies to be transparent about their data collection, usage, and sharing practices, our findings provide important insights into how fully informed consumers respond to online personalized advertising. When personalization practices are overt, people do not accept and resist personalized advertising based on private information, that involve sharing of personal data, and higher, personalized pricing. Declaration of interests

The authors declare that they have no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chbhr.2021.100144.

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