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RESEARCH PAPER

The effects of targeted political advertising on user privacy concerns and digital product acceptance: A preference-based approach

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Abstract
Online businesses are increasingly relying on targeted advertisements as a revenue stream, which might lead to privacy concerns and hinder product adoption. Therefore, it is crucial for online companies to understand which types of targeted advertisements consumers will accept. In recent years, users have been increasingly targeted by political advertisements, which has caused adverse reactions in media and society. Nonetheless, few studies experimentally investigate user privacy concerns and their role in acceptance decisions in response to targeted political advertisements. To fill this gap, we explore the magnitude of privacy concerns towards targeted political ads compared to "traditional" targeting in the product context. Surprisingly, we find no notable differences in privacy concerns between these data use purposes. In the next step, user preferences over ad types are elicited with the help of a discrete choice experiment in the mobile app adoption context. Our findings suggest that while targeted political advertising is somewhat less desirable than targeted product advertising, the odds of choosing an app are statistically insignificant between two data use purposes. Together, these results contribute to a better understanding of users' privacy concerns and preferences in the context of targeted political advertising online.

Keywords Online privacy · Targeting · Advertisement · DCE

JEL classification M37

Introduction

Online companies commonly serve advertisements to their customers as a revenue strategy (Kim & Kim, 2017). In recent years, advances in computing technologies have enabled companies to collect and process large amounts of user data to make these advertisements increasingly personalized (Zhu et al. 2023; Bleier & Eisenbeiss, 2015). By analyzing user data, online advertising can be targeted to customers' demographics, preferences, and interests, making the ads more effective and, therefore, more attractive to advertisers (Acquisti et al., 2016; Farahat & Bailey, 2012). Research has also shown that users may find targeted advertising more useful (Bleier & Eisenbeiss, 2015). However, in some cases, users may perceive targeted advertising as intrusive and express heightened privacy concerns (Boerman et al., 2017), which could hinder product adoption and lead to consumer backlash (Zhu et al., 2023; Chen et al., 2019). Hence, it is crucial for online businesses to understand the type of targeted advertising that users will accept.

The dichotomy between perceiving personalized advertisement as useful on the one hand and privacy intrusive on the other has been termed the personalization-privacy paradox (Sutanto et al., 2013). So far, research in this area has mostly focused on user attitudes toward commercial advertising (Chiasson et al., 2018; Bleier & Eisenbeiss, 2015; Walrave et al., 2018). However, users are increasingly targeted online with highly personalized advertising for political campaigns as well. At the same time, little is known about how customers react to the use of their data for

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political advertising in terms of their privacy concerns and their product adoption intentions.

With spending on online political campaigning having skyrocketed in recent years (Spenkuch & Toniatti, 2018), making up a third of the ad spending of the 2022 U.S. midterm elections (Statista, 2023) as well as almost the entire budget of the "Vote Leave" campaign prior to the Brexit referendum in 2016 (Wong, 2018) the topic of targeted political online advertising is a hotly debated issue in media and society (Zuiderveen Borgesius et al., 2018). Some scholars regard the use of personal data as a threat to democracy (Persily, 2017), the free exchange of political ideas (Tucker et al., 2018), and voter polarization (Sunstein, 2018). Public media has voiced similar concerns, stating that targeted political advertising "might work too well" by presenting recipients with individually tailored election promises (Wong, 2018; Fowler, 2020). Further, the practice of targeting political ads to voters has been acknowledged as "unethical" (Graham-Harrison et al., 2018) and "immoral" (Vidler, 2018). Overall, the intensity of the discussion on political targeting online seems to indicate that privacy concerns about the use of personal data for political ads are significant and possibly greater than privacy concerns about targeting in product ads[1].

But not only the media are concerned about targeted political advertisements. Similar developments are taking place in the European and US legal contexts. The General Data Protection Regulation (GDPR) introduced in the European Union prohibits the use of data for purposes other than those originally stated in the consent form (GDPR, 2016). In addition, UK politicians and human rights organizations call for greater transparency in the use of personal data for targeted political advertising (Galaski, 2022, Hern, 2018). In Germany, data collected for political purposes must fulfill stricter requirements than data collected for commercial use (Kruschinski & Haller, 2017). Moreover, regulation in the United States tightens the requirements for political advertisers, but not other advertisers, to target consumers online (Lapowsky, 2018).

However, research findings on users' acceptance of these advertisements remain limited. First empirical evidence shows that these developments might reflect public opinion. While 62% of U.S. respondents indicate that using data to present targeted political advertising is unacceptable, only 47% say the same about product ads (Smith, 2018). Moreover, public opinion polls show that the majority of Americans would prefer social media platforms to stop showing political ads (Auxier, 2020).

[1] While "traditional" targeted online ads can be used to promote products, services, brands, and/or companies, in this study we refer to these commercial uses as "product ads" to simplify the presentation.

Taken together, these observations suggest that (1) the use purpose of data collected for targeting might influence privacy concerns, and (2) attitudes towards political targeting might be more negative than towards targeting for other purposes. Nonetheless, it remains unclear whether people actually have greater privacy concerns when it comes to using their information for political purposes compared to other types of targeted marketing.

Research that examined consumer attitudes toward targeted advertising through the lens of the personalization-privacy paradox suggests that the acceptance of personalization depends on several contextual factors such as communication channel (Zhu et al., 2023), being primed to think about privacy (John et al., 2011) or perceived control over one's information (Xu et al. 2012). We suggest data use purpose might be an additional contextual factor that could impact how much data users are willing to share for personalized advertisements. So far, only a few studies have investigated the role of use purpose of data collection in personal data valuation and privacy concerns (Zhu et al., 2023; Sheng et al., 2008). Preliminary research suggests that the purpose for which data is collected is crucial to consumers, with political entities being viewed more negatively as recipients of personal data than commercial entities (Tan et al., 2018; Kozyreva et al., 2021). This is particularly relevant in the context of the GDPR legislation, which strictly requires companies to specify the purpose of data collection and prohibits other uses (GDPR, 2016). To the best of our knowledge, no experimental study so far has systematically studied user acceptance of data collection for political advertisements as opposed to product advertisements. In this vein, our paper sheds light on the neglected aspects of targeted political advertising: the effects of use purpose of data collection on user privacy concerns and acceptance of digital products. Specifically, we address the following research question:

RQ1: Are privacy concerns greater when data is collected for political advertising than when it is collected for product advertising?

Past studies show that stated privacy concerns and actual privacy behaviors are not always correlated (Dinev et al., 2015; Baruh et al., 2017; Yu et al., 2020). In fact, users frequently act contrary to their privacy concerns when faced with real-life decisions (Acquisti et al., 2015). Therefore, this study examines users' acceptance of targeted political advertisements beyond privacy concerns and includes people's choice behavior. We further ask:

RQ2: How does the intention to adopt differ between products that process user data for targeted political advertising and targeted product advertising?

Our contribution is twofold: First, we add to the existing IS privacy literature by investigating the relevance of use purpose in the study of user privacy concerns through the lens of the personalization-privacy paradox (Belanger & Crossler, 2011; Sutanto et al., 2013). While previous research has looked at various determinants of privacy concerns with online products, such as anonymity (Schomakers et al., 2020), transparency (Betzing et al., 2020), or social cues and trust (Zalmanson et al., 2022), data use purpose has received limited attention so far. Second, our results can assist online businesses in understanding acceptable data collection practices from the viewpoint of their users. Specifically, in study 1, we directly elicit and compare user privacy concerns about the use of different personal data items for political and product targeting. This enables us to address whether concerns about their personal data depend on these two different use purposes. In study 2, we apply the Discrete Choice Experiment (DCE) methodology (Derikx et al., 2016; Ebbers et al., 2021) to elicit users' stated preferences over targeted ad types in a choice scenario that approximates a real-life situation more closely than the setting in study 1. Indeed, the DCE approach allows for a better understanding of whether the use of user information for targeted political advertising has a substantial impact on the choice behavior of consumers and is, therefore, of high importance for practitioners.

Both studies were pre-registered at the Center for Open Science and Data. Instructions are available in the repository linked to the project.[2]

Theoretical background

Privacy concerns and targeted advertisement: The personalization-privacy paradox

Adopting the definition of privacy concerns by Hong and Thong (2013, p. 267) as "the degree to which an Internet user is concerned about website practices related to the collection and use of his or her personal information," we draw on the literature on the personalization-privacy paradox to understand how these concerns might differ between targeted political and targeted product advertising. The personalization-privacy paradox suggests that while users tend to have greater privacy concerns about advertising when it is targeted, they also see value in it (Angst & Agarwal, 2009; Sutanto et al. 2013). So far, most of this research has focused on the "traditional" marketing context, in which targeted ads are used to improve the reach and effectiveness of online product marketing (Acquisti et al., 2016; Farahat & Bailey, 2012) as well as consumer perceptions regarding specific products, services, or brands (Boerman et al., 2017). In these commercial contexts, consumers have been shown to perceive personalized advertisements as more useful (Bleier & Eisenbeiss, 2015), direct more attention toward such ads, exhibit a greater intention to forward them (Walrave et al., 2018), and are more likely to click on them (Aguirre et al., 2015). Consequently, this elevates the effectiveness of the message in terms of product purchase intentions (Tucker, 2014) and positive attitudes toward the promoted brand (Walrave et al., 2018). For example, Hirsh et al. (2012) show that personality-based targeting increases the acceptance and effect of the message to the consumer. Similarly, advertising based on users' interests has been shown to lead to a higher acceptance and success rate (De Keyzer et al., 2015; Tucker, 2014) as well as click-through rates (Boerman et al., 2017).

At the same time, while users see value in targeting, most people do not wish to receive ads that are targeted to their interests (Boerman et al., 2017) or online activities (Chiasson et al., 2018). As such, these privacy concerns are rooted in practices of collecting and using personal data (Moore et al. 2015), forwarding it to third parties (Sutanto et al., 2013), and tracking individuals over several websites (Antón et al., 2010). For example, users have been shown to oppose targeting that is based solely on the analysis of their individual data as compared to aggregate data (Dolin et al., 2018). They are also more reluctant to share information with websites that show targeted ads when it makes them personally identifiable (e.g., phone number, address, social security number, exact current location) and when it includes financial details than when it includes only basic demographic information (e.g., country, gender, age) (Chiasson at al., 2018; Leon et al., 2013). Potential reasons why users might be opposed to their data being used for targeting advertisements to them include them becoming aware of the attempted persuasion, making them feel manipulated (Bleier & Eisenbeiss, 2015), and being deprived of their freedom of choice (Tucker, 2012). Further, targeted advertising increases perceived intrusiveness (van Doorn & Hoekstra, 2013). Together, these results suggest that despite the potential relevance of targeted ads for users, privacy concerns are central to understanding user acceptance and attitudes toward them (Sutanto et al., 2013).

To date, only a small number of studies have examined the acceptance of personalized advertisements in the political context. Surveys report on differences in acceptance of targeted product advertisements and targeted political advertisements. For example, 62% of US respondents regard the

[2] Available here: https://osf.io/3knuv/?view_only=2e7b28a8fce04e85a5034d7e6a2108a8.

use of their data to show them targeted political advertising as unacceptable, while only 47% state the same about commercial ads (Smith, 2018). Further, a survey study among participants from the USA, UK, and Germany shows that acceptance of target political advertisements is lower than acceptance of target product advertisements (Kozyreva et al., 2021). Moreover, 54% of surveyed Americans state that social media platforms should not be allowed to show any political advertisements (Auxier, 2020). Together, these results suggest that privacy concerns between targeted product and targeted political advertisements might differ. Theoretical reasons for this will be discussed in the next sections.

Context as a determinant of privacy attitudes

Past literature has established that privacy concerns vary with contextual factors (Acquisti et al., 2015; Zhu et al., 2023). Hence, whether a person accepts the personalization of advertising messages in exchange for providing personal data may depend on the situation. Recently, researchers have emphasized the importance of systematically studying context when examining consumers' privacy attitudes, adopting the perspective that privacy is a malleable state of being intertwined with its context (Zhu et al., 2023; Xu & Zang, 2022; Zu & Kanjanamekanant, 2021). Through this lens, an individual's privacy preferences are not the result of a fixed set of rules that weigh the costs and benefits of data disclosure, but rather, they are highly volatile and subject to change depending on factors such as social norms, emotions, and heuristics (Acquisti et al., 2015). The reasons for this may lie in the nature of the privacy decision-making itself: Privacy harms are often intangible and accompanied by information asymmetries and, therefore, not easily understood by consumers (Acquisti et al., 2015). Further, even when aware of the risks and benefits of data disclosure, people might still have malleable privacy preferences as people, in general, have difficulties deciding how much they like products or services (Slovic, 1995), with privacy being no exception (Acquisti et al., 2015). In addition, individuals might experience cognitive distortions when assessing the benefits and costs of privacy decisions (Acquisti et al., 2013). All of these factors contribute to a high level of uncertainty when forming privacy concerns or engaging in decisions that involve privacy trade-offs (Acquisti et al., 2015). Research has shown that in situations that are highly uncertain, individuals turn to contextual cues for guidance, which makes privacy concerns a function of their context (Xu & Zhang, 2022). Hence, an individual might display extreme privacy concerns in one setting, but slight changes in the environment could result in a substantial relaxation of these concerns. In the realm of privacy research, a context is characterized by factors that shape all situational opportunities and constraints, such as the type of information used, the entities involved, or how the data is processed (Nissenbaum, 2009; Xu & Zhang, 2022).

Numerous studies have demonstrated that privacy concerns are context dependent. For example, the privacy concerns of individuals will be different if their data is processed in the cloud or on a client-side basis (Kobsa et al., 2016). Further, users express heightened privacy concerns when the data for personalization originates from third parties other than the website they are visiting at that moment (John et al., 2018; Zhu & Kanjanamekanant, 2021). In addition, counterintuitively, people are less willing to disclose their data on professional websites versus unprofessional-looking ones (John et al., 2011). Exogenous changes in the context that alter the default settings also impact privacy behavior: When Facebook changed its visibility settings such that publicly displaying a user's high school became the default, a stark increase in people doing so was observed (Stutzman et al., 2013). In sum, these results show that the acceptance of targeted advertising depends on different contextual cues, and the purpose of data collection for either product or political advertisements is potentially one of them.

Data use purpose as a contextual factor

Extending the findings on the context as a determinant of privacy attitudes, we propose that users' privacy concerns might differ depending on whether their data is being used in the context of target political or targeted product advertisements. However, only a few studies so far have investigated the use purpose of personal data as a contextual factor potentially determining privacy valuation. This is of high practical relevance, however, since the GDPR and international privacy guidelines by the OECD stipulate that companies make any use purpose salient to consumers during data collection (purpose specification principle) and generally use personal data only for purposes compatible with this purpose (purpose limitation principle).

Extant research suggests that personal data use purpose alters people's acceptance of personalized advertisements. For example, Sheng et al. (2008) show that people express greater privacy concerns when services are personalized for the purpose of nonemergency information versus emergency alerts like natural disasters. More recently, Zhu et al. (2023) found that participants perceived personalized advertisements as less privacy-preserving when their data was being used for advertisements in private versus in the work context. Further, studies show that when data is collected for the purpose of secondary use by third parties, users express greater privacy concerns (Potoglou et al., 2013; Preibusch, 2015). When measuring the valuation of personal data depending on the recipient who uses the data, Tan et al. (2018) found that participants are less likely to sell their personal data to a political party than to an advertising network. Surprisingly,

Table 1 Instructions for participants in Study 1

Same for both treatments
Imagine the following situation: You have registered on a free video streaming platform. On this online platform, users can set up a profile page, upload videos and watch videos of others. Users can engage with creators and other viewers through comments, messages and chats. To provide free service, this platform shows ads to its users. The ads are personalized based on the data users share (e.g., on their profile page), their behavior on the platform, and the information that can be inferred from that. This means that an ad's message is individually adapted to its recipient. Therefore, users see differently phrased advertisements based on the data they provided.
Treatment 1: Product advertising
Now imagine you are shown a product ad on this platform. For example, you are shown an ad that promotes a specific feature of a product. How concerned are you if the following data gathered on the platform is used to personalize this ad to you:
Treatment 2: Political advertising
Now imagine you are shown a political ad on this platform. For example, you are shown an ad that promotes a specific campaign promise of a politician or political party. How concerned are you if the following data gathered on the platform is used to personalize this ad to you:

when it comes to health-related information, people are more willing to disclose it to the public and certain third parties than to friends and family (Prasad et al., 2012). Kozyreva et al. (2021) report that survey participants find the use of private data for commercial purposes more acceptable than for political purposes. However, responses could have been subject to demand effects, as participants stated attitudes towards political as well as product ads.

Together, past studies have examined people's attitudes toward data use purpose in the domains of emergency situations (Sheng et al., 2008), work versus private messages (Zhu et al., 2023), third-party usage (Potoglou et al., 2013; Preibusch, 2015), and being sold to political parties (Tan et al., 2018), supporting the notion that the purpose for which personal data is used plays a significant role in users' privacy attitudes and decision-making process. So far, most studies that compared attitudes toward targeted political and targeted product advertisements are observational (Kozyreva et al., 2021; Smith, 2018). Therefore, research remains limited, calling for more experimental studies in this context. Against this background, we experimentally explore the extent of users' privacy concerns and their attitudes toward targeted political ads compared to targeted product ads.

Research overview

We conduct two studies that test for differences in users' privacy concerns and product adoption intention between targeted political advertisements and targeted product advertisements. In study 1, a vignette experiment, 300 participants revealed their privacy concerns toward a digital service that either used their data for targeted political or targeted product advertisements. In study 2, 297 respondents stated their intention to adopt an app that showed them either targeted political or targeted product advertisements in a discrete choice experiment.

Study 1: Vignette experiment

Motivation

In light of sparse research evidence and given the public discussion of online political advertising, understanding if consumers perceive use purpose differently is highly important for multiple stakeholders, including internet companies and legislators. Indeed, Bode and Jones (2018) show empirically that privacy concerns and public support for stronger privacy regulation are closely intertwined and that effective legislative action has to address the most pressing concerns of constituents. Further, Angst and Agarwal (2009) have argued that understanding users' privacy concerns is imperative to understanding their adoption of services. Hence, in study 1, we contribute to understanding purpose-dependent privacy concerns. Specifically, we test whether users have stronger privacy concerns when they are informed that their data is used for targeted political advertising compared to targeted commercial advertising. This research question is related to works by Kozyreva et al. (2021), Tan et al. (2018), and Chiasson et al. (2018), who find that concern for sensitive data is related to its use.

Methods and participants

We used a between-subject design in the form of vignettes. This type of design allows for the measurement of perceptions in a reliable and valid way and has been widely used in IS research (Dennis et al., 2012; Siponen & Vance, 2010). In both conditions, participants were presented with a fictional video streaming platform that collects users' personal data in order to target different ads (see Table 1). In treatment 1, participants were presented with a situation in which the data was collected to target product advertisements. In treatment 2, the data was used to target advertisements for a politician or political campaign. Hence, participants were only presented with one of the possible purposes for which their data is used to mitigate concerns over experimenter demand effects (Charness et al., 2012). One hundred fifty-one participants were randomly assigned to treatment 1, and 149 participants to treatment 2. The instructions that were presented to participants are available in Table 1.

The item list was constructed based on previous research on privacy concerns with regard to certain data items (Melicher et al., 2016). Participants indicated their concern if a specific given item on the list was used to personalize an advertisement to them. Participants could indicate their level of concern on a 5-point scale with 1 = unconcerned to 5 = very concerned (Krasnova et al., 2013). Moreover, the option "cannot judge" has been added to complete the range of possible answers. In total, 16 items were presented (Leon et al., 2013). An overview of the items is in Table 2. The order of items was randomized. We also collected data about age, education, gender, social media use, and the use of an ad-blocker. Running balancing checks for the two treatments revealed no statistically significant differences for any demographic categories between the two groups. This suggests a balanced assignment to treatments.

We recruited 300 mTurk workers. That sample size gave us sufficient power to pick up a small effect of 0.3 standard deviations with 80% power. The survey that mTurk-participants completed took slightly more than 7 minutes (mean= 7 min 27 s, median= 6 min 21 s). Data was collected using Qualtrics (Peer et al., 2012). To avoid selection bias, we gave no information about the purpose of the study on mTurk. Workers were, on average, 34.7 years old. 39.2% of the participants were female. 44.0% held a Bachelor's degree. 98.2% of participants reported being active social media users, and 91.7% reported sharing information on social media at least very rarely. However, only 10.8% of participants reported doing so daily or multiple times a day.

Results

We performed a two-sided independent samples t-test to check for differences between the level of concern in the targeted product and the targeted political ads condition. The t-tests were run for all 16 items on the list. Four "cannot judge" responses ($N = 1$ for religious views, $N = 2$ for political views, and $N = 1$ for browsing) were excluded. Our results (Table 2) indicate that participants are equally concerned about targeted political advertising vs. targeted product advertising. None of the differences across the 16 items we tested is significantly different from 0 at conventional significance levels.

Discussion

We find no evidence for increased privacy concerns when personal data is used for targeted political advertising compared to targeted product advertising. As such, these findings

Table 2 Differences in privacy concerns between the product (treatment 1) and political (treatment 2) targeting scenarios

Data items	Mean privacy concerns (1 = unconcerned, 5 = very concerned)		Difference of means	Standard error	p -value	t -value
	When personal data is collected for targeted *product* ads	When personal data is collected for targeted *political* ads				
Current location	3.49	3.24	0.25	0.17	0.131	1.511
Current place of residency	3.34	3.26	0.07	0.17	0.668	0.429
Income	3.19	3.14	0.05	0.16	0.744	0.327
Family status	2.98	2.93	0.05	0.16	0.772	0.289
Browsing	2.62	2.75	− 0.13	0.16	0.407	− 0.830
Occupation	2.62	2.59	0.03	0.16	0.855	0.182
Political views	2.62	2.53	0.09	0.16	0.570	0.568
Religious views	2.48	2.45	0.04	0.17	0.828	0.217
Followings	2.37	2.47	− 0.10	0.16	0.511	− 0.658
Education	2.36	2.31	0.04	0.15	0.768	0.295
Videos	2.29	2.36	− 0.07	0.16	0.668	− 0.429
Followers	2.21	2.37	− 0.16	0.16	0.298	− 1.043
Likes	2.11	2.33	− 0.22	0.15	0.154	− 1.428
Age	2.07	2.20	− 0.14	0.15	0.380	− 0.879
Subscriptions	2.01	2.23	− 0.22	0.14	0.136	− 1.496
Gender	1.81	2.03	− 0.22	0.14	0.111	1.598

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, $N = 151$ in treatment 1, $N = 149$ in treatment 2

counter the assumption that the purpose of data collection, specifically the usage of user information for political purposes, is an important determinant of privacy concerns in the specific case we investigated. Nevertheless, past research questions the external validity of privacy concerns elicited in surveys (Woodruff et al., 2014). Further, these findings do not allow us to draw wide-ranging conclusions regarding user preferences. Indeed, the setting of study 1 did not allow us to see if specific user concerns regarding different types of targeting have a differential impact on user acceptance preferences/decisions. In fact, it could be that while observed levels of concern do not differ between the use for targeted political and product ads, user willingness to adopt a product that uses personal data for targeted political advertising is lower. On the other hand, one may also argue that these hypothetical differences in behavioral impact might be driven by stronger opinions regarding political advertising in general and might not be related to information usage per se (targeting). To disentangle these effects, study 2 was conducted.

Study 2: Discrete choice experiment

Motivation

In study 2, we further explore our initial research question with a DCE commonly employed to reveal user preferences (e.g., Ebbers et al., 2021; Abramova, 2022). Specifically, we investigate whether there are any differences in user preferences regarding the use of their information for targeted political and targeted product ads. By applying a DCE, we are able to (i) measure user preferences over targeted advertising in the political vs. commercial (product) domain, as well as (ii) explore user preferences over targeted vs. non-targeted ads in both contexts.

Methodology

The DCE approach is based on a combination of two elements: (1) discrete choice analysis to model preferences and (2) stated preference methods to gather the required data for eliciting these preferences (Kjaer, 2005; Street & Burgess, 2007; Viney et al., 2002). Stated preference methods allow researchers to specify consumer preferences in hypothetical but close-to-the-truth scenarios. It helps to disentangle the influence of discrete attributes in the choices made by respondents and derive the valuation of these attributes. Due to its consistency with the economic demand theory, DCE is preferred over other conjoint methods, which are purely mathematical (Louviere et al., 2010). Another element of DCE, discrete choice analysis, is rooted in the Random Utility Theory (RUT) (Manski, 1977; McFadden, 1973), which considers a rational individual who chooses between several alternatives consistently and maximizes his/her own utility. In line with the economic theory of value, goods in a DCE are perceived as a bundle of attributes because "these characteristics give rise to utility" (Lancaster, 1966, p. 163). Consequently, the utility of a good is the sum of the utilities of its individual attributes. The probability that a particular alternative is chosen depends on the estimated utility discrepancy among alternatives caused by differences in utility for each attribute. Moreover, it is possible to estimate a consumer's marginal willingness to pay (WTP) for a change in the level of an attribute, assuming that the vector of attributes includes costs (Kjaer, 2005).

Model specification

We focused on a fictional scenario of a mobile streaming app, "Hi.tube." To increase the attractiveness of the app and thereby create a balanced trade-off between ads as the (negative) attribute of interest and other characteristics (Krasnova et al., 2014; Rose & Bliemer, 2007), the app description stated that it would employ a novel data compression technology that reduces mobile data usage. The app was presented in the following way "*Please read the following text presenting you an app called "HI.tube." It works for Android as well as Apple iOS. This is what the app does: HI.tube is a streaming app which allows you to watch videos on a large number of topics (similar to YouTube, Netflix, or Showbox). Wherever you are, whether on the way to work, waiting in a long queue or relaxing at home sofa, with Hi.tube you will never be bored! With Hi.tube you can upload your own videos, or watch videos other users created. You can engage with our growing Hi.tube community by following other users, commenting or liking videos, and messaging them. Another advantage of Hi.tube is a new method of data compression which significantly reduces mobile Internet usage and is therefore optimal while commuting! Enjoy millions of videos, channels and playlists in high-quality – always and everywhere using the minimum of mobile Internet!*".

Conducting a DCE involves three key stages: (1) model specification; (2) experimental design, and; (3) questionnaire development (Rose & Bliemer, 2007). In the model specification stage, the selection of attributes and levels was based on the pretest with 50 mTurk workers. It revealed that the most important characteristics of the "Hi.tube" app, in descending order, include being ad-free, offering unlimited streaming, and enabling background play when the mobile device is locked. The average perceived usefulness of an app (Krasnova et al., 2014) was moderately high (mean = 2.94 on a 5-point Likert scale). Following findings on critical features behind the app adoption from the pretest, the following attributes were included in the main experiment, namely (1) the advertisement plan of an app, (2) price as a monetary

Table 3 Attributes and levels as presented to the respondents

Feature	Levels
Ad plan	1. No ads: You do not see any ads on the platform. 2. Product ads—untargeted: In this case, you see video ads for different products. The ads you see are not targeted, which means that your personal information is not used at any point in time to select the ad shown to you. All users of the app see the same product ads. 3. Product ads—targeted: in this case, you see video ads for different products that are specifically targeted to you based on your viewing history and interaction with the app. It works in the following way: based on the videos you have already viewed, the app infers what interests and buying preferences you might have. For example, imagine you watched a few videos on healthy cooking in the past days. The app now concludes you strive a healthy lifestyle. When you open the app today to watch a video, the app will show you an ad promoting a healthy granola bar, or membership in a new fitness club, or a new protein diet. 4. Political ads—untargeted: in this case, you see video ads for different political campaigns or candidates. The ads you see are not targeted, which means that your personal information is not used at any point in time to select the ad shown to you. All users of the app see the same political ads. 5. Political ads—targeted: in this case, you see video ads for different political campaigns or candidates that are specifically targeted to you based on your viewing history and interaction with the app. It works in the following way: based on the videos you have already viewed, the app infers what interests and political beliefs you might have. For example, imagine you watched a few videos on healthy cooking in the past days. The app now concludes you strive a healthy lifestyle. When you open the app today to watch a video, the app will show you an ad of a political campaign supporting the introduction of a tax on sugary drinks; or an ad promoting a political candidate who supports a bill for reducing taxes on healthy products. 6. Local events ads—targeted: in this case, you only see ads for local events that are specifically targeted to you based on your viewing history and interaction with the app. It works in the following way: Based on the videos you have already viewed, the app infers which concerts or workshops might be interesting to you. For example, imagine you watched a few videos on healthy cooking in the past days. The app now concludes you strive a healthy lifestyle. When you open the app today to watch a video, the app will show you an ad of a cooking workshop that focuses on “clean eating”.
Streaming limit	1. 1 h per day 2. 3 h per day 3. Unlimited
Price	1. free 2. $ 1.00 3. $ 3.00

cost, and finally (3) streaming limit (to vary perceived benefit of an app). The levels for the attributes were chosen as follows (see Table 3):

Advertising plan is the attribute in the focus of our analysis and simultaneously the most important one to users. Levels were designed with the aim of answering our research questions. Ad free was set as the baseline level. The other levels varied in terms of ad domain (political versus commercial (product) and targeting (no targeting versus targeting). An additional level of targeted ads for local events was introduced to decrease choices in the fractional factorial design from 90 to 36. Examples were chosen such that for each ad domain, the viewed video and induced interest remained fixed, but only the resulting ad varied. For the political ad, the bi-partisan topic of food taxes was chosen in order to mitigate the effects of political affiliation.

Price: Following our pretest, the maximum willingness to pay for the app without ads, unlimited streaming, and background play was $3.00 USD (median). Hence, we decided to set price levels to $0.00 USD (free), $1.00 USD, and $3.00 USD.

Streaming limit: Unlimited streaming was rated as the second most important feature of the app in the pretest.

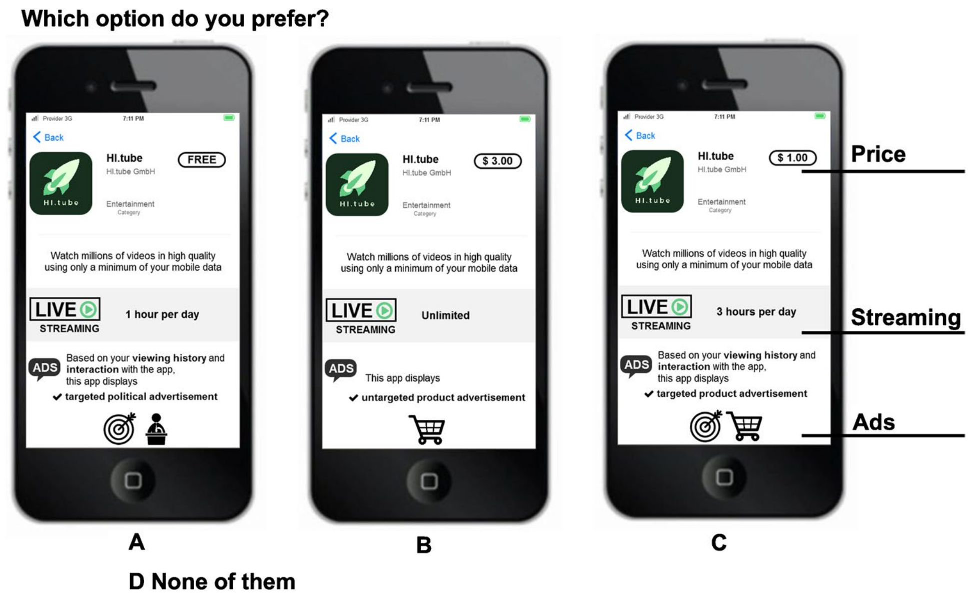


Fig. 1 An image of the mock-ups that were presented to the participants

Unlimited streaming was therefore set as the upper bound. One and 3-h daily access were chosen for the other levels considering the app was presented as being useful for commuting. Average daily commuting times to work are approximately 50 min (US Census Bureau, 2021).

Table 3 gives an overview of attributes and levels as presented to respondents.

Experimental design and questionnaire creation

Upon accessing the survey, respondents were presented with a detailed description of the video streaming app, its functionality, and its value proposition, as described above. Next, the main features of the HI.tube app, i.e., attributes and their corresponding levels, were presented as shown in Table 3. Acknowledging that not all users may clearly understand the specificity of different advertisement plans, we provided examples of how a particular ad type works and made respondents spend at least 1 minute on the page. Next, 12 choice sets (the sequence of the presentation was randomized) were presented for evaluation by the respondents. The number of choice sets was derived via the D-efficient design, resulting in 12 choice sets per person, with each choice set consisting of 3 alternatives (see Fig. 1). Specifically, in each choice set, respondents were asked to choose one app that they would install ("Which option do you prefer?") with possible answers A, B, or C, and a "no choice" option ("None of them") to cover situations where none of the presented streaming apps was acceptable for a respondent. Finally, we asked respondents several questions about their demographics, privacy concerns, and attitudes towards targeted and untargeted advertisements, experienced misuse of their personal data online, and degree of political involvement.

Sampling

We recruited 297 mTurk workers. During recruitment, workers who took part in study 1 or in the pretest were excluded. To check for fatigue and other confounds, a manipulation check was incorporated, with the 12th choice card including an alternative that was strictly dominant. Participants who did not pass this manipulation check or always chose the "no choice" option were excluded from further analysis ($N = 33$). The average duration of filling out the survey was slightly more than 12 min (mean = 12 min 17 s; median = 10 min 13 s). Participants who completed the survey in less than 5 min were excluded from the analysis ($N = 2$).

In total, 262 responses were used in the final analysis. This number surpasses the minimum sample size recommended in Orme (2006), which is 83 for our model. To avoid selection bias, we gave no information about the purpose of the study on mTurk. 50.7% of our sample were female, and 50.3% were male, 42% held a Bachelor's degree. Participants were, on average, 38.5 years old. Providing evidence for favorable attitudes towards the Hi.tube app among respondents, the average perceived usefulness of the app reached 5.20 (SD = 1.31) assessed on a 7-point scale (Krasnova et al., 2014). Respondents reported being moderately engaged in politics (mean = 5.01, SD = 1.32) on a 7-point scale (Zhang & Bartol, 2010). Moreover, reported privacy concerns can be classified as moderate to high (mean = 5.22, SD = 1.42), measured on a 7-point scale (Krasnova et al., 2009).

Table 4 Model estimates and marginal willingness to pay (MWTP) for the total sample ($N = 262$)

Attribute	Attribute level	Mixed logit		Conditional logit	
		Estimate	MWTP	Estimate	MWTP
Streaming limit	1 h per day	Reference level		Reference level	
	3 h per day	0.93***	$0.38	0.58***	$0.62
	Unlimited	2.59***	$1.05	1.50***	$1.60
Ad plan	No ads	Reference level		Reference level	
	Untargeted product ads	− 1.09***	− $0.44	− 0.73***	− $0.78
	Targeted product ads	− 1.45***	− $0.59	− 0.95***	− $1.01
	Untargeted political ads	− 1.50***	− $0.61	− 0.87***	− $0.93
	Targeted political ads	− 1.89***	− $0.77	− 1.07***	− $1.14
	Targeted local ads	− 1.37***	− $0.56	− 0.93***	− $0.99
Price	Price of the app	− 2.46***		− 0.94***	
GoF	Adjusted Estrella	0.76		0.72	
	McFadden's pseudo R2	0.40		0.37	

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Results

Model estimates and marginal willingness to pay

The data were analyzed using a mixed logit model, considered the most promising state of the art available when working with choice-based data since a random error term adjusts for individual-specific variations in preferences (Hauber et al., 2016). In our case, the utility function of a participant i choosing an app alternative j in a choice set t looks as:

$$U_{jit} = c_j + \beta_1 Price + \beta_2 DailyStreamingPlan + \beta_3 AdvertisementPlan + \mu_i + \varepsilon_{jit} \tag{1}$$

where μ is the error component with the normal distribution with zero mean and standard deviation σ_μ which varied across app alternatives j and respondent i and accounted for the correlations between observations obtained from the same respondent. The error component ε assumed to follow the Gumbell distribution with mean = 0 and accounted for differences between respondents, app alternatives and choice sets. Normal mixing distribution for price was assumed, and all attributes except price were dummy-coded (Table 4, mixed logit).

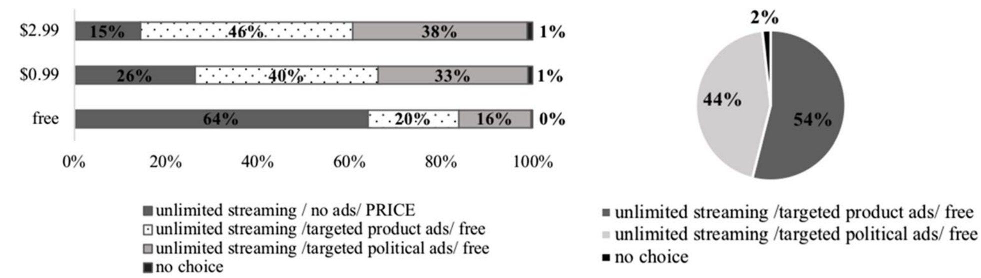
Goodness-of-fit (GoF) measures provide evidence that the proposed model fits the data well. Our estimation results illustrate that all attributes included in our model are important for potential consumers. For example, the unlimited streaming plan ($\beta = 2.59, p < 0.001$) and the price of the app ($\beta = -2.46, p < 0.001$) substantially determine decision-making. The coefficients for different advertisement plans are negative and significant, indicating users' perception of advertising as an adverse feature. Coefficients can be interpreted as follows: on average, for a level change in one attribute (e.g., 3 h per day streaming) compared to the reference level (i.e., 1 h per day streaming), the odds of choosing a product with this attribute level (i.e., 3 h per day streaming) over a product with an attribute at the reference level increase by a factor of exp(β) (i.e., exp (0.93) = 2.53 meaning 153% increase), while holding other variables constant. Given this, our results suggest that, on average, the odds of choosing an app with *untargeted product ads* over a no-ads app decrease by 66% (i.e., a factor of exp(− 1.09) ≈ 0.34) while holding other variables constant. Integrating *targeted product ads* into an app decreases the odds of choosing this product by 77% (i.e., exp(− 1.45) ≈ 0.23). The odds of choosing a product with *untargeted political ads* over an ad-free alternative decrease by 78%. Approximately 85% decrease in chances of being chosen is observed for an app with *targeted political ads* compared to an ad-free product.

After estimating the effect of various attribute levels on the user's utility, we also computed the marginal willingness to pay (MWTP) for a change in the attribute level according to the following formula (Kjaer, 2005, Ryan et al., 2007):

$$\text{MWTP} = \frac{\beta_{\text{attribute}}}{-\beta_{\text{price}}} \tag{2}$$

Negative MWTP values can thus be interpreted as a required reduction in price to offset the downgrade to the inferior feature (Table 4).

Here it is important to note that in the absence of an alternative for a coefficient comparison test suitable for the mixed model and integrated in SAS, inferences on the differences between attribute levels were made on the basis of direct comparisons of MWTP for specific attribute levels and market share simulations. First, as expected, we observe that respondents show negative attitudes towards targeting, favoring untargeted over targeted ads for both political ($MWTPuntarg = -\$0.61$ vs. $MWTPtarg = -\$0.77$) and product ($MWTPuntarg = -\$0.44$ vs. $MWTPtarg = -\$0.59$)



(a) Simulation including an ad-free type

(b) Simulation with two ad-types

Fig. 2 Results of the market simulations based on participants' preferences

contexts. Second, differences in preferences are observed concerning the purpose of data use. Compared to the "no ads" scenario, users would ask for a $0.59 discount to accept an app that uses their data for the targeted product ads. Targeted political ads are viewed as slightly more undesirable by respondents and would require a $0.77 compensation.

Market simulations

To further explore differences in user concerns regarding targeted political ads and targeted product ads, we simulated consumer choices for certain app alternatives. Market shares were extrapolated via the mixed logit model, where initial estimates served as a starting point (see Table 4). To explore the effect of the type of targeted ads, we ran a series of simulations comparing three different apps. All apps offered unlimited streaming, yet only (1) is ad-free while, (2) contains targeted product ads, and (3) contains targeted political ads. Throughout all simulations, (2) and (3) remain free for users, whereas the price for (1) varies between free, $0.99, and $2.99. Moreover, the option "no choice" is available. Results are presented in Fig. 2a.

The results of the simulations suggest that when all three options are free, 64% of respondents prefer an ad-free version, 20% select the option with targeted product ads, and 16% choose the option with targeted political ads. Increasing the price of the ad-free option to $0.99 and $2.99 strongly influences choices, rendering the ad-free version highly undesirable. More importantly, market shares of app versions with targeted ads increase respectively: when the price of an ad-free app reaches $2.99, the market share of an app with targeted product advertising reaches 46%, while the market share of the app with targeted political advertising follows closely, reaching 38%.

In the second simulation (Fig. 2b, two apps were contrasted: a free app with unlimited streaming and targeted product ads vs. a free app with unlimited streaming and targeted political ads. We observe that while the app with targeted product ads will dominate the market with a market share of 54% vs. 44% for the option with targeted political ads, this dominance is very unstable due to users' extreme price sensitivity. Once the alternative with targeted product advertising is priced at $0.99, its market share decreases to 25%, and the overwhelming majority (72%) switches to the free app with targeted political advertising.

Together, these findings cautiously suggest that while targeted political advertising is perceived as somewhat less desirable by respondents, their usage does not consequentially deter users from choosing such an app, with user preferences being highly volatile.

Robustness check: Alternative model and additional evidence

The analysis using a mixed logit model provides evidence for comparably small differences in users' preferences towards targeted product ads and targeted political ads, with the latter being perceived as more negative. Although observable, these differences do not appear to be particularly pronounced. Hence, as a robustness check, we have computed conditional logit model estimates (Table 4, conditional logit). As such, this approach does not account for the individual heterogeneity between respondents (and therefore is inferior to mixed logit modeling) but allows us to easily integrate a check for coefficients' equality in SAS. In this case, the utility function of a participant choosing an app alternative in a choice set looks as:

$$U_{jt} = c_j + \beta_1 Price + \beta_2 Daily\ Streaming\ Plan + \beta_3 Advertisement\ Plan + \varepsilon_{jt} \tag{3}$$

The core findings remained the same, pointing to the estimated effects being insensitive to changes in model specifications.

For the conditional logit model, the statistical significance of the difference between two coefficients can be tested using the Wald test (see Table 5). The pairwise comparison suggests significant differences between targeted vs. untargeted advertisements for both product ($Ho : \beta_{\text{TargProductAds}} = \beta_{\text{UntargProductAds}}$, Wald statistic = 5.63, Pr > ChiSq = 0.018) and political advertising plans ($Ho : \beta_{\text{TargPoliticalAds}} = \beta_{\text{UntargPoliticalAds}}$, Wald statistic = 3.99, Pr > ChiSq = 0.046). At the same time, we find

Table 5 Pairwise assessment of whether the difference between coefficients is statistically significant

	Untargeted product ads	Targeted product ads	Untargeted political ads
Untargeted product ads	–	–	–
Targeted product ads	**Significant** 5.63/0.018	–	–
Untargeted political ads	Insignificant 1.92/0.166	Insignificant 0.71/0.399	–
Targeted political ads	**Significant** 12.49/0.0004	Insignificant 2.31/0.129	**Significant** 3.99/0.046

The 1st number is the Wald statistic/the 2nd number is Pr > ChiSq

no significant differences with regard to the advertising plan type for both targeted ($Ho: \beta_{\mathrm{TargProductAds}} = \beta_{\mathrm{TargPoliticalAds}}$, Wald statistic = 2.31, Pr > ChiSq = 0.129) and untargeted ($Ho: \beta_{\mathrm{UntargProductAds}} = \beta_{\mathrm{UntargPoliticalAds}}$, Wald statistic = 1.92, Pr > ChiSq = 0.166) ads.

Summarizing, the analysis of the conditional logit model suggests that both targeted product and targeted political ads are judged as more negative than respective untargeted ads. Further, while users appear to show slight preferences towards targeted product ads compared to targeted political ads based on MWTP or choice simulations (see Table 4, conditional logit), these differences are not statistically significant. As such, these findings corroborate our results of study 1.

Discussion, contributions, and limitations

Two studies reported in this paper explore users' privacy concerns and preferences regarding the use of their data either for the targeted product or political ads. Interestingly, despite heated, mainly negative, media discussions surrounding the use of personal data for political targeting, we find that respondents in study 1 do not exhibit a higher level of privacy concern regarding targeted political advertising than targeted product advertising. We, therefore, negate RQ1 (Are privacy concerns greater when data is collected for political advertising than when it is collected for product advertising?).

Study 2 tested preferences over ad types in the form of real choice behavior when installing a fictional streaming app. Overall, the experiment shows that an average participant performs the traditional privacy calculus, weighing app-specific benefits against personalized ads and monetary costs (e.g., Betzing et al. 2020; Xu et al. 2011). Based on a conditional logit model analysis, we show that both targeted product ads and targeted political ads are judged more negatively than respective untargeted ads. Further, findings from our main analysis (mixed logit model) suggest that while targeted political advertising is perceived as somewhat less desirable by respondents, their usage does not consequentially deter users from choosing such an app. Moreover, these preferences are highly volatile once the price of a competing app changes. Further, statistical tests conducted with a conditional logit model find no significant differences between user preferences towards targeted ads in both domains. Together, addressing RQ2 (How does the intention to adopt differ between products that process user data for targeted political advertising and targeted product advertising?), our results suggest that people are opposed to targeting in general. Although our respondents were slightly more reluctant to use an app with political ads than for product ads (both targeted and untargeted), the difference is statistically insignificant.

Theoretical implications

Our findings contribute to the IS literature in several ways. First, our study adds to the literature on the personalization-privacy paradox (Angst & Agarwal, 2009; Sutanto et al., 2013) by shedding light on the data use purpose as a contextual factor driving privacy concerns. Several studies have documented that the use purpose as a contextual factor impacts privacy preferences (Sheng et al., 2008; Potoglou et al., 2013; Preibusch, 2015; Tan et al., 2018; Zhu et al., 2023). For example, a recent study by Zhu et al. (2023) found that communication channel, device, and business vs. private purpose predicted users' perceived privacy concerns. Results show that users were less concerned when their Facebook messenger data were used to display targeted ads for a business trip accommodation compared to targeted ads for a family tour package. Focusing on other data use purposes (targeted product vs. targeted political ads), we report insignificant differences in the effects on privacy concerns when asked directly in a vignette survey (study 1) and indirectly in a stated choice experiment (study 2).

Second, we extend the literature on advertising personalization (Acquisti et al., 2016; Farahat & Bailey, 2012, Werner et al., 2022) by showing that users accept targeted political advertising to the same extent as targeted commercial advertising but hold slightly less favorable views about targeted than untargeted ads in general. While earlier studies indicate that people prefer personalization in some cases (Ebbers et al., 2021) and show that personalized advertisement significantly increases website stickiness (Werner et al., 2022), we corroborate studies that show that users respond less positively to advertisements when personally identifiable information is used for targeting (e.g., Sutanto et al., 2013; Ho & Bodoff, 2014; Tsekouras et al., 2016; Balan & Mathew, 2022).

Third, we show that targeted political advertising is another area where people's stated preferences in surveys (Kozyreva et al., 2021) diverge from revealed choice behavior. While participants claim they dislike political targeting in surveys (Kozyreva et al., 2021), our DCE results show that when faced with a decision scenario, they do not differentiate between targeted political and targeted product advertisements.

Finally, this paper broadly enriches privacy research in e-commerce and precisely the "E-commerce benefits and consumer privacy" theme in the taxonomy of Bandara et al. (2019). We experimentally verified the relevance of the privacy calculus lens for an average user (Dinev et al., 2015): our respondents were sensitive to the benefits of a digital product (streaming limit) as well as to monetary (price) and non-monetary costs (ads). While Betzing et al. (2020) report that transparently disclosed privacy policies insignificantly affect acceptance rates of consent to the use of personal data, we show that a disclosed ad plan (e.g., using data for targeted political purposes) significantly affected the probability of choosing an offer. Still, the sensitivity towards various advertisement plans was relatively low compared to price.

Practical implications

Our findings inform online businesses about acceptable data collection practices from a user perspective. Study 1 (Table 2) ranges a comprehensive list of data items based on how much they drive privacy concerns. By understanding what information users find acceptable to share and being transparent about data usage upfront, online businesses can establish trust and credibility with their users, to increase user engagement and loyalty.

Next, this paper suggests that people informed about how their data will be used (e.g., for targeted marketing or political ad campaigns) tend to find data collection for various purposes equally acceptable or non-acceptable. Policymakers can benefit from these findings to shape regulations and assess the effectiveness of already existing policies related to data collection practices like the GDPR, emphasizing the importance of transparency and disclosure requirements for businesses rather than focusing solely on the purpose of data collection. Suppliers of digital products can provide clear and concise disclosure about data usage, not being afraid that this information would drop acceptance.

Limitations

Our study has several limitations. In the absence of an alternative for the coefficient comparison test suitable for the mixed model in SAS, inferences on the differences between attribute levels were made based on direct comparisons of MWTP for specific attribute levels and market share simulations. Hence, the conditional logit model provided additional insights concerning the statistical significance of observed differences. This approach, however, does not account for the individual heterogeneity between respondents and is, therefore, inferior to mixed logit modeling. Further, one potentially important limitation of the DCE is the assumption of rationality, thus calling for control for behavioral biases.

As another limitation, we relied on two US mTurk samples for our study. Samples from online panels such as mTurk offer important advantages over student samples, as they are more diverse and more closely reflect the overall population (Buhrmester et al., 2011). However, while the effects observed in mTurk samples typically replicate in general population samples (Chandler et al., 2019; Coppock et al., 2018), mTurkers are still demographically different from the general US population, with samples being younger, more liberal, and better educated (Chandler et al., 2019). This is also true for both of our samples. Further, 98% of the participants in our samples say they use social media, which is a higher rate than observed in the general population (Auxier, 2020). However, since our research question addresses a topic relevant to internet and social media users, we consider this sample adequate for our purposes. As previous research shows that mTurk-workers might be more sensitive about unanonymized data than a representative US sample (Kang et al., 2014), we would expect our results to replicate in a general population sample since their privacy concerns could be even lower. Although we took precautions to ensure data quality (Buhrmester et al., 2011), further research is needed to show if our results hold for other samples like general population samples. Further, a cross-cultural comparison with European attitudes could be informative to provide a deeper understanding of users' concerns. In addition, adding different examples of targeted political advertising that also address the specific nature of negative political advertising could potentially be of interest. In this paper, we deliberately avoided those examples to mitigate the potential effects of partisanship, yet future research could loosen this restriction. Together, these limitations offer exciting venues for future research.

Conclusion

A vast majority of digital products rely heavily on personal data, simultaneously posing a threat to the users' privacy. We respond to the heated public debate around employing user data for politically targeted advertisements and the European Union's General Data Protection Regulation (GDPR), which advocates for users' rights to be informed about the purpose of their data use. A vignette survey and a discrete choice experiment show that targeted political vs. product advertisements result in insignificant differences in privacy concerns and preferences for digital products. We confirm significant user preference for untargeted ads over targeted ads regardless of domain. While publicly displayed preferences towards political targeting in ads are very negative, revealed choices point to insignificant differences compared to targeting for commercial purposes.

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