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Katharina Baum
University of Potsdam, katharina.baum@uni-potsdam.de

Stefan Meißner
Norwegian School of Economics, stefan.meissner@nhh.no

Olga Abramova
University of Potsdam, oabramov@uni-potsdam.de

Hanna Krasnova
University of Potsdam, krasnova@uni-potsdam.de

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Research paper

Katharina Baum, University of Potsdam, Potsdam, Germany, katharina.baum@uni-potsdam.de

Stefan Meißner, Norwegian School of Economics, Bergen, Norway, stefan.meissner@nhh.no

Olga Abramova, University of Potsdam, Potsdam, Germany, oabramov@uni-potsdam.de

Hanna Krasnova, University of Potsdam, Potsdam, Germany, krasnova@uni-potsdam.de

Abstract

Reliance on targeted political ads has skyrocketed in recent years, leading to negative reactions in media and society. Nonetheless, only few studies investigate user privacy concerns and their role in user acceptance decisions in the context of online political targeting. To fill this gap, in this study 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 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. Among others, our findings from simulations on the basis of a mixed logit model cautiously suggest that while targeted political advertising is perceived as somewhat less desirable by respondents, its presence does not consequentially deter users from choosing such an app, with user preferences being highly volatile. 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, political ads, DCE

1 Introduction

With spending on online political campaigning skyrocketing in recent years (Spenkuch and Toniatti, 2018), making up about 20% of the campaign expenses in the last presidential (Wong, 2018) and midterm elections (Schouten, 2018) in the United States, 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). Public media has voiced concerns that targeted political advertising "might work too well", presenting recipients with individually tailored election promises (Wong, 2018). In this debate, the use of personal data for targeted political advertising is viewed as a breach of privacy, and consequentially, on a more global level, as a threat to democracy (Persily, 2017), free exchange of political ideas (Tucker et al., 2018), and voters' polarization (Sunstein, 2018). Media has called the practice of targeting political ads to voters "unethical" (Graham-Harrison et al., 2018) and "immoral" (Vidler, 2018). Recent articles on the upcoming presidential campaign in the United States have voiced alarm about apps that collect information and subsequently "sell it to a political candidate who can then surround you with messages" (Halper, 2019). Overall, the intensity of the media 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 towards targeting in other settings, such as in product ads[1]. Importantly, critical opinions on political targeting go beyond news articles, as a joint effort by U.S. tech magazine Wired and the non-profit organization ProPublica shows. By collecting all political advertisements on Facebook and their corresponding target groups they aim to inform citizens about which of their personal data is used for political ads they see (Kelly, 2018). Similar developments are observed in Europe's legal context, with UK politicians requesting more transparency regarding the use of personal information for targeted political advertising (Hern, 2018). In Germany, data collected for political purposes already has to fulfil stricter requirements than data collected for commercial use (Kruschinski and Haller, 2017). Further, the General Data Protection Regulation (GDPR) introduced in the European Union prohibits the use of data for any other purpose than the one that was originally stated in a consent form (GDPR 2018). Moreover, a new regulation was also introduced in the United States that tightens requirements for political, but not other advertisers if they want to target consumers online (Lapowsky, 2018).

Research findings, however, remain limited. First empirical evidence shows that these developments might reflect public opinion. While 62% of US respondents indicate that using data to present targeted political advertising is unacceptable, only 47% say the same about product ads (Smith, 2018). In addition, preliminary research results support the assumption that the purpose for which data is collected is important to consumers, with political entities as recipients being regarded more negatively than commercial ones (Tan et al., 2018).

Altogether, these observations on politicians and non-profits demanding more transparency regarding data use for political targeting, the existing regulations as well as some first empirical findings hint towards a common direction: Use purpose of data collected for targeting might influence privacy concerns, and 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 the use of their information for political purposes in comparison to other types of targeted marketing. While previous studies have focused on eliciting privacy concerns regarding the use of personal data in the context of "traditional" online product advertising (Chanchary et al., 2018; Leon et al., 2013), no study to the best of our knowledge has systematically studied the magnitude of user privacy concerns in the context of political campaigning. In addition, only few studies have investigated the role of use purpose of data collection in personal data valuation and privacy concerns. This seems especially relevant against the background of the new GDPR legislation, which strictly requires companies to specify the purpose of their data collection and prohibits any other uses (GDPR, 2018).

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[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.

This paper therefore sets out to explore the magnitude of user privacy concerns and preferences in the context of targeted political advertisement. Our contribution is twofold: First, we add to the existing privacy literature by investigating the relevance of use purpose in the context of user privacy concerns, and second, we inform practitioners about the impact that data use for targeted political ads may have on adoption decisions of their customers.

Specifically, in study 1 we directly elicit and compare user privacy concerns with regard to the use of different personal data items for political and "traditional" product targeting. This enables us to address the open question if people have a different level of concern with regard to their personal data depending on these two use purposes. As past research questions the external validity of privacy concerns derived from such measures (Woodruff et al., 2014), in study 2 we apply the Discrete Choice Experiment (DCE) methodology in order to elicit user 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 behaviour of consumers and is therefore of high importance for practitioners.

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

The remaining part of the paper is structured as follows. In chapter 2 related literature is discussed. Study 1 is presented in chapter 3, followed by study 2 in chapter 4. Chapter 5 discusses overall results and gives concluding remarks. In chapter 6, limitations are discussed.

2   Related work

2.1   Targeted Online Advertisement

Different ways of targeted ads have been used in practice and studied in research. Types of targeting can be differentiated in multiple ways, including the amount and type of data used (Aguirre et al., 2015; Boerman et al., 2017; Doorn and Hoekstra, 2013; Walrave et al., 2018), whether only individual or aggregate user data is used (Dolin et al., 2018), or whether targeting specifically addresses the personality of a user (Hirsh et al., 2012). Further, the way of how user data is aggregated and how interests are inferred differs between targeting types. For example, contextual targeting refers to the practice of placing an ad related to the content of the web-site a user currently visits (Doorn and Hoekstra, 2013). With remarketed targeting, the user is tracked over several websites and receives an ad for a product that was looked at before (Samat et al., 2017). Interest based targeting also tracks the user over several websites, but then an ad for a product that is similar to the products previously viewed is presented (Samat et al, 2017).

2.2   Targeting in Product Advertisement

So far, most research on targeted advertising has focused on the "traditional" marketing context, in which targeted ads are used to improve the reach and effectiveness of product online marketing (Acquisti et al., 2016; Farahat and Bailey, 2012) as well as consumer perceptions regarding specific products, services, or brands (Boerman et al., 2017). This research is best described through the prism of the personalization paradox – the phenomenon that suggests that while users tend to attribute higher privacy concerns to targeted ads, they also see value in them (Angst and Agarwal, 2009; Sutanto et al., 2013). Indeed, consumers have been shown to perceive self-relevant advertisement as more useful (Bleier and Eisenbeiss, 2015), direct more attention towards such ads, exhibit greater intention to forward them (Walrave et al., 2018), and are more likely to click on them (Aguirre et al., 2015). Consequently, this elevates effectiveness of the message in terms of product purchase intentions (Tucker, 2014), and positive attitudes towards 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.

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

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 (Bleier and Eisenbeiss, 2015), most people do not wish to receive ads that are targeted to their interests (Boerman et al., 2017) or online activities (Chanchary 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 (Anton et al., 2010). For example, users have been shown to oppose targeting that is based solely on the analysis of their individual data as opposed to aggregate data (Dolin et al., 2018); and seem 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) (Chanchary at al., 2018; Leon et al., 2013). Apparently, recipients of targeted ads are more likely to become aware of the attempted persuasion, making them feel manipulated (Bleier and Eisenbeiss, 2015), and deprived of their freedom of choice (Tucker, 2012). Further studies show that targeted advertising increases perceived intrusiveness (Doorn and Hoekstra, 2013), and can lead to reactance among viewers (Doorn and Hoekstra, 2013). In a similar vein, Tucker (2014) documents that while interest-based targeting is associated with the increased level of ad success on Facebook, this out-come is dependent on the perceived level of a privacy threat to the user. Together, this suggests that despite their potential relevance for users, privacy concerns are central in understanding user acceptance and attitudes towards targeted ads (Sutanto et al., 2013).

2.3   Targeting in Political Advertisement

While the effects of political advertising have been extensively studied (Spenkuch and Toniatti, 2018), their effect in terms of voters' turnout and individual voting decisions among constituents has not been clearly established. For example, while some studies conclude that political TV ads have a magnifying effect on the total voters' turnout (Freedman et al., 2004), others show the opposite effect (Gordon and Hartmann, 2016; Krasno and Green, 2008). In their newest study, Spenkuch and Toniatti (2018) find that political TV ads in the 2004, 2008, and 2012 elections have altered the partisan composition among voters, while having almost no effect on overall turnout.

Driven by the explosive reliance on online targeting in the context of recent political campaigns (Schouten, 2018; Wong, 2018), recent studies have started to make first strides in exploring its effectiveness in the online domain. Here, limited research evidence provides evidence for the effectiveness of targeted online political ads in affecting voters' behaviour. For example, Liberini et al. (2018) report that online campaigns on Facebook, targeted to users based on gender, location, and partisanship, significantly increased the likelihood of undecided voters to vote for a specific candidate. In addition, they increased turnout of core republicans by five to ten percentage points, while having no effect on Democrats or Independent voters. Further, research suggests that the effect of individual posts can be large, with an extra of 340,000 citizens participating in the 2010 U.S. congress elections after seeing a Facebook post urging people to vote (Bond et al., 2012). At the same time, there is first evidence that targeted political ads appear to raise concerns among their recipients. For example, a phone survey done in 2012 revealed that more than 80% of U.S. adults reject targeted political online ads and would be angry if Facebook showed them political ads based on their profile. Moreover, 64% of respondents state that they would be less likely to vote for a candidate who uses targeted ads (Turow et al., 2012). Since then awareness of targeting practices has increased (Samat et al., 2017), possibly further influencing user attitudes. Nonetheless, existing research in this domain remains limited. To fill this gap, in this study we set out to explore the level of users' privacy concerns and their acceptance of targeted political ads in comparison to product ads.

2.4   Valuation of Information Privacy and Data Use Purpose

With the amount of data consumers share online increasing exponentially, the value users attach to their privacy has been in the focus of many scholarly articles over the past years for (reviews see: Acquisti et

al, 2015; Bélanger and Crossler, 2011; Smith et al., 2011). Specifically, research has investigated the value users' attach to their data in general (Krasnova and Kift, 2012), as well as to specific data items (Grossklags and Acquisti, 2007), others' data (Pu and Grossklags, 2015), contextual factors (John et al., 2011) and cognitive biases (Acquisti et al., 2012) as determinants of users' disclosure, as well as personality traits as antecedents of privacy attitudes (Staiano et al., 2014).

However, only few studies have investigated the use purpose of personal data as a factor determining privacy valuation so far. This is of high relevance, however, since GDPR as well as international privacy guidelines by the OECD stipulate that companies make any use purpose salient to consumers at the time of data collection (purpose specification principle) and generally use personal data only for purposes compatible with this purpose (purpose limitation principle). For example, in this context, some studies show that secondary use by third parties is of importance to consumers, leading to greater privacy concerns (Potoglou et al., 2013; Preibusch, 2015). When measuring the valuation of personal data depending on its recipient Tan et al. (2018) find that participants are less likely to sell their personal data to a political party than to an advertising network. Surprisingly, when it comes to health-related information, people are more willing to disclose to the public and certain third parties than to friends and family (Prasad et al., 2012). Further, the study by Cvrcek et al. (2006) finds that respondents place higher value on their data when it is used for commercial purposes than solely for academic purposes, with the use purpose being more relevant than quantity and time horizon of data collection (Cvrcek et al., 2006). Together, these results all point towards the direction that the purpose for which personal data is used plays a significant role in users' privacy attitudes and decision-making process. However, research remains limited, calling for more studies in this context. Against this background, in this study we set out to explore the level of users' privacy concerns and their attitudes towards targeted political ads (in comparison to "traditional" targeted product ads).

3 Study 1

3.1 Motivation and Research Question

In the light of sparse research evidence and given the public discussion of online political advertising, understanding if that purpose is perceived differently by consumers is of high importance 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 the understanding of purpose-dependent privacy concerns with regards to targeted political advertising. 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 work that has been conducted by Tan et al. (2018) and Chanchary et al. (2018) that finds that concern for sensitive data is related to the use of it.

3.2 Methods and Participants

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 sec, median: 6 min 21 sec). 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. About 39.2% of participants were female. 98.2% of participants reported to be active social media users and 91.7% of the participants reported sharing information on social media at least very rarely. Yet, only 10.8% of participants reported doing so daily or multiple times daily. We used a between-subject design. In both conditions, a fictional video streaming platform collecting users' personal data to target different ads was presented (see Table 1). In treatment 1, participants were presented with a situation in which the data was collected to target product

advertisement. In treatment 2, the data was used to target advertisement 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). 151 participants were randomized into treatment 1 and 149 participants were randomized into treatment 2. The instructions that were presented to participants are available in Table 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:

Table 1.   Instructions for participants in Study 1

The item list was constructed based on previous research on privacy concerns with regards 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 five-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 provided 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 of the demographic categories between the two groups. This suggests a balanced assignment to treatments.

3.3   Results

The main results are presented in Table 2. We performed a two-sided t-test to check for differences between the level of concern in the product and the political condition. This test was 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 indicate that participants are not significantly more concerned with regard to targeted political advertising compared to targeted product advertising. None of the differences across the 16 items we tested is statistically significantly different from 0 at conventional significance levels. Further, exploratory tests with a one-sided t-test revealed no differences at a 5% significance level. However, results reveal significant differences within each item list that are in line with previous literature. For example, consistent with Leon et al. (2013), participants were more concerned about the use of their current location data compared to information about their gender ($\Delta = 1.44***$, p = 0.000). As such, this is a strong indication for the validity of stated concern levels as the patterns replicate past findings.

Data Items	Mean		Difference	Standard Errors	p-value	t-value
	Product	Political				
Current Place of Residency	3.34	3.26	0.07	0.17	0.668	0.429
Current Location	3.49	3.24	0.25	0.17	0.131	1.511
Age	2.07	2.20	-0.14	0.15	0.380	-0.879
Gender	1.81	2.03	-0.22	0.14	0.111	-1.598
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
Occupation	2.62	2.59	0.03	0.16	0.855	0.182
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
Religious Views	2.48	2.45	0.04	0.17	0.828	0.217
Political Views	2.62	2.53	0.09	0.16	0.570	0.568
Followings	2.37	2.47	-0.10	0.16	0.511	-0.658
Subscriptions	2.01	2.23	-0.22	0.14	0.136	-1.496
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
Browsing	2.62	2.75	-0.13	0.16	0.407	-0.830

Independent t-test [*] $p < 0.05$, [**] $p < 0.01$, [***] $p < 0.001$, N=151 Treatment 1, N=149 Treatment 2

Table 2.   Differences in privacy concerns between the political and the product targeting scenarios

3.4   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 run counter to 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 to draw wide-ranging conclusions regarding user preferences. Indeed, the setting of study 1 did not allow 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 the case that while observed levels of concerns 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 the fact of information usage per se (targeting). To disentangle these effects, study 2 was conducted.

4   Study 2

4.1   Motivation

In study 2 we further explore our initial research question with a DCE. 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 these both contexts.

4.2   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 and 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 a number of alternatives in a consistent manner 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 discrepancy in utilities among alternatives caused by differences in utility for each attribute. Moreover, it is possible to estimate a consumers' marginal willingness-to-pay (WTP) for a change in the level of an attribute assuming that the vector of attributes includes costs (Kjaer, 2005).

4.3   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 and Bliemer, 2008), 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 the mobile Internet usage and is therefore optimal while commuting! Enjoy millions videos, channels and playlists in high-quality – always and everywhere using minimum of mobile Internet!"*.

Conducting a DCE involves three key stages: (1) model specification; (2) experimental design, and; (3) questionnaire development (Rose and Bliemer, 2008; Johnson et al., 2013). In the model specification stage, the selection of attributes and levels was based on the pre-test 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 pre-test, the following attributes were included in the main experiment, namely (1) the advertisement plan of an app, (2) price as a monetary 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 therefore 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 (McIntere, 2018) was chosen in order to mitigate 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 rated as the second most important feature of the app in the pre-test. Unlimited streaming was therefore set as the upper bound. 1 and 3 hour 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 minutes (US Census Bureau, 2016).

Table 3 gives an overview of attributes and levels as presented to 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 hour per day 2. 3 hours per day 3. Unlimited
Price	1. free 2. $ 1.00 3. $ 3.00

Table 3. Study 2: Attributes and levels as presented to the respondents.

4.4 Experimental Design and Questionnaire Creation

Upon accessing the survey, respondents were presented with the 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 the fact that not all users may have exact understanding of the specificity of different advertisements plans, we provided examples on how a particular ad type works and forced respondents to spend at least 1 minute on the page. Next, 12 choice sets (the sequence of presentation was randomized) were presented for evaluation to 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 Figure 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 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 advertisement, experienced misuse of their personal data online, and degree of political involvement.
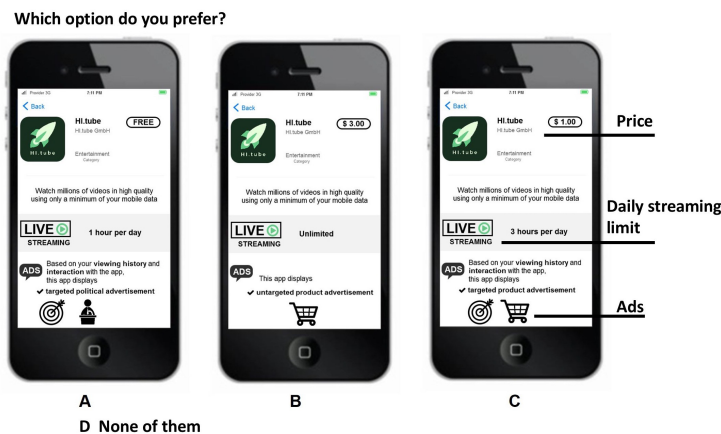

Figure 1: An image of the mock-ups that were presented to the participants

4.5 Sampling

We recruited 297 mTurk workers. During recruitment, workers who took part in study 1 or in the pre-test 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 sec; median=10 min 13 sec). Participants who completed the survey in less than 5 minutes 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 (2010) 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. Participants were on average 38.5 years old. Providing evidence for favorable attitudes towards the Hi.tube app among respondents, an average perceived usefulness of an app reached 5.20 (SD=1.31) assessed on a 7-point scale (Krasnova et al., 2014). Respondents reported to be moderately engaged in politics (mean=5.01, SD=1.32) on a 7-point-scale (Zhang and 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).

4.6   Results

4.6.1   Model Estimates and Marginal Willingness to Pay

The data was analysed using a mixed logit model which is considered to be 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: $U_{jit} = c_j + \beta_1 Price + \beta_2 DailyStreamingPlan + \beta_3 AdvertisementPlan + \mu_i + \varepsilon_{jit}$, where μ s 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. Normal mixing distribution for price was assumed, and all attributes except price were dummy-coded (Table 4, mixed logit).

Attribute	Attribute Level	Mixed logit		Conditional logit	
		Estimate	MWTP	Estimate	MWTP
Streaming Limit	1 hour per day	Reference Level		Reference Level	
	3 hours 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	

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

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

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, unlimited streaming plan ($\beta = 2.59$, $p < 0.000$) and the price of the app ($\beta = -2.46$, $p < 0.000$) substantially determine decision-making. The coefficients for different advertisement plans are negative and significant, indicating users' perception of advertising as an adverse feature. 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 (Kjær, 2005, Ryan et al., 2008): $TP = \frac{\beta_{attribute}}{-\beta_{price}}$. Negative MWTP values can thus be interpreted as a required reduction in price to offset for the downgrade to the inferior feature. Here it is important to note that in the absence of an alternative for coefficient comparison test suitable for the mixed model and integrated in SAS, inferences on the differences between attribute levels were done 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 ($MWTP_{untarg} = -\$0.61$ vs. $MWTP_{targ} = -\$0.77$) and product ($MWTP_{untarg} = -\$0.44$ vs. $MWTP_{targ} = -\$0.59$) contexts. Second, differences in preferences are observed with regard to 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.

4.6.2   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 Figure 2 (a).

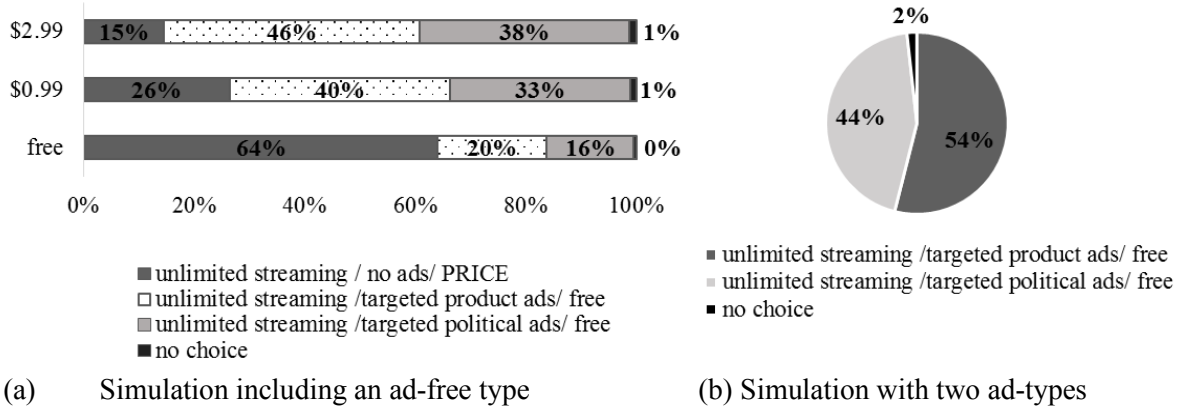(a)   Simulation including an ad-free type   (b) Simulation with two ad-types

Figure 2: Results of the market simulations based on responses of participants

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 (Figure 2 (b), 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.

4.6.3   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 difference do not appear to be particularly pronounced. Hence, to gain additional insights, 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 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: $U_{jt} = c_j + \beta_1 Price + \beta_2 \, Daily \, Streaming \, Plan + \beta_3 Advertisement \, Plan + \varepsilon_{jt}$. With this approach, differences between two coefficients can be tested using the Wald-test. The pairwise comparison suggests significant differences for targeted vs. untargeted advertisement for both product ($Ho: \beta_{\text{Targ Product Ads}} = \beta_{\text{Untarg Product Ads}}$, ChiSq=5.63, Pr > ChiSq=0.0176) and political advertising plans

$(Ho: \beta_{\text{Targ Political Ads}} = \beta_{\text{Untarg Prolitical Ads}}$, ChiSq=3.99, Pr > ChiSq=0.049). At the same time, we find no significant differences with regard to the advertising plan type for both targeted $(Ho: \beta_{\text{Targ Product Ads}} = \beta_{\text{Targ Political Ads}}$, ChiSq=2.31, Pr > ChiSq=0.1286) and untargeted $(Ho: \beta_{\text{Untarg Product Ads}} = \beta_{\text{Untarg Political Ads}}$, ChiSq=1.92, Pr > ChiSq=0.1663) 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 in comparison 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.

5　Discussion and Concluding Remarks

Both studies reported in this paper explore users' privacy concerns and preferences regarding the use of their data either for targeted product or political ads. Interestingly, despite heated 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 with regard to targeted political advertising in comparison to targeted product advertising.

Study 2 tested preferences over ad types in the form of real choice behavior when installing a fictional streaming app. On the basis of conditional logit model analysis, we show that both targeted product and political ads are judged as more negatively than respective untargeted ads. Further, findings from our main analysis (mixed logit model) 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. Moreover, these preferences are highly volatile once the price of a competing app changes. Further, statistical tests conducted with a conditional logit model approach find no significant differences between user preferences towards targeted ads in both domains. Together, our results cautiously suggest that people are opposed to targeting in general and possibly a little more so for political than for product ads. Nonetheless, our findings from both the mixed logit and conditional logit models should be interpreted with caution, calling for further investigation in order to obtain more robust results.

Overall, based on two empirical studies, our findings contribute to a better understanding of users' privacy concerns and preferences in the context of targeted political advertising online.

6　Limitations

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

As another limitation, we only recruited participants from a single participant pool. Previous research shows that mTurk-workers might be more sensitive with regard to unanonymized data than a representative US-sample (R. Kang et al., 2014). 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. For example, a cross-cultural comparison with European attitudes could be informative to provide a deeper understanding of users' concerns. Further, 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 potential effects of partisanship, yet future research could loosen this restriction. Together, these limitations offer exciting venues for future research.

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