New Strategies in Data-driven Marketing: Consumer Data-Sharing and Personalization in the Post-Third-Party Cookie Era

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Abstract:

This research explores the transformation in digital marketing due to the elimination of third-party cookies, mainly driven by browser providers. We focus on the use of zero-party data, which consumers willingly provide. The study investigates the effect of personalization on the willingness of consumers to share various types of personal data and identifies the most sensitive. We conducted a preliminary online survey, which provides initial insights into consumers' making data-sharing decisions, emphasizing the inherent cost-benefit trade-off underlined by social exchange theory. The early findings reveal a higher tendency of users to share socio-demographic data but exhibit reluctance in sharing data about social media interactions. We provide insights for practitioners and researchers in digital marketing. Acknowledging the study's limitations, we propose future research avenues to deepen the understanding of how consumers value their data in the context of personalization.

Keywords: Personalization, cookie-less future, zero-party data

Track: Digital Marketing & Social Media

1. Digital marketing in the post-cookie era – a shift towards zero-party data

The evolution of personalization in digital marketing is transforming with the increasing digitalization, advanced artificial intelligence, and shifting perspectives on privacy trade-offs (Davenport, 2023). Meta CEO Mark Zuckerberg has recently acknowledged a trend of diminished data availability for personalized ads due to Apple's IDFA opt-in overhaul, sparking a public dispute (HEC Paris Insights, 2022). Divergent privacy practices emerged when Meta introduced a subscription model for ad-free content in Europe in October 2023 (Meta, 2023). Legal frameworks like the 'EU General Data Protection Regulation' (GDPR) also address global privacy concerns (Skiera et al., 2022). Another significant development is the phase-out of third-party cookies (Johnson, Runge, and Seufert, 2022), which resemble one of the most important cornerstones of data-driven targeting. Google's announcement of 'Cookiecalypse' highlights this by entailing Chrome banning cookies by the end of 2024 (Chavez, 2022). Approximately 83 percent of the browser market, including Chrome, Safari, and Mozilla, is projected to abandon third-party cookies in the following year (Statcounter, 2023), considerably affecting how marketers personalize campaigns (Skiera et al., 2022). This paradigm shift in digital marketing prompts an essential question: What strategies can be adopted for data-driven marketing post-third-party cookie era? This concern is a primary focus for marketers and a key area in the Marketing Science Institute's research agenda for 2022-2024, aligning with both managerial and academic interests (MSI, 2022).

In light of these developments, companies are revamping their data strategies, for instance, by utilizing zero-party data, which consumers voluntarily share with firms (Rowan, 2020; Martin & Palmatier, 2020). This strategic shift focuses on customer-centricity, developing direct relationships, and data collection through proprietary channels. Focusing on generating digital data-driven marketing strategies in the post-cookie era, our research aims to answer: i) How does personalization influence a consumer's decision to share different personal data? ii) Which data type do emerge as the most cost-intensive?

We explore consumers' trade-offs between personalization and data sharing, emphasizing zero-party data and drawing on social exchange theory. We analyze data collected through an online survey, revealing a first conceptual understanding and setting the stage for larger-scale investigations and field experiments. We provide insights for firms seeking to align their digital marketing strategies with consumer privacy considerations and to create value through personalized experiences.

2. The balancing act between personalization versus privacy

In digital marketing, personalization is the process of tailoring products, communication, services, and user experiences to match individual preferences (Davenport, 2023), fulfilling consumers' desire for added value (Goldfarb & Tucker, 2011). However, effective personalization relies on a firm's data collection and processing capabilities and consumers' willingness to share data (Martin & Palmatier, 2020). Although consumers generally appreciate personalization efforts, research has shown they are often unwilling to provide the necessary information (Aguirre, Mahr, Grewal, de Ruyter, and Wetzels, 2015). This reluctance has been described as the personalization-privacy paradox (Awad & Krishnan, 2006). Literature on personalization underscores privacy concerns arising from the trade-off between personalized benefits and data-sharing risks (Martin & Murphy, 2017). In line with social exchange theory (e.g., Homan, 1961), scholars primarily characterize the decision to receive personalized offerings as consumers weighing the benefits against the discomfort of sharing personal data (Krafft, Arden, and Verhoef, 2017; Schumann, von Wangenheim, and Groene, 2014).

Personalization and privacy considerations are crucial in various marketing domains, such as retailing, e-commerce, and social networks. Most prior research in this area has focused on privacy in the context of personalized online advertising (e.g., Bleier & Eisenbeis, 2015; Goldfarb & Tucker, 2011; Schumann et al., 2014), as well as on topics like permission or consent management (e.g., Skiera et al., 2022; Krafft et al., 2017) and the design of information requests (e.g., Bidler, Zimmerman, Schumann, and Widjaja, 2020).

Our study focuses on consumers' trade-offs between different personalization offerings, i.e., benefits, and different data, i.e., costs. This research aims to contribute insights into the dynamics of consumer data valuation, shedding light on the varying value of data types. The focus on zero-party data – explicitly including different data types – has not yet been explored (Martin & Murphy, 2017; Martin & Palmatier, 2020).

3. Zero-party data for personalization in digital marketing

In designing tailored digital marketing strategies, firms have traditionally relied on third-party cookies to track cross-website user behavior (Skiera et al., 2022). Previously, data privacy policies were less stringent, allowing firms to use cookies more freely without significant legal or ethical effects (Davenport, 2023). The prevalent use of third-party cookies offers convenience and scale, enabling broad audience targeting without requiring extensive direct interactions (Johnson et al., 2022). However, rising privacy concerns prompt firms to prioritize alternative data types, emphasizing transparent marketing, user consent, and value exchanges for direct customer relationships (Martin & Palmatier, 2020). A significant portion of data is accessible through consumer self-disclosure, a proactive action where consumers authorize firms to access information (Martin, Borah, Palmatier, 2017). One way is that firms acquire zero-party data by consumers voluntarily sharing information in exchange for valuable offerings like personalization (Martin & Palmatier, 2020). Hence, zero-party data gathering operates transparently as consumers have complete control over the disclosure, facilitating exchanges driven by perceived value and aligned with privacy security (Martin & Palmatier, 2020). Since prior studies show that transparency and control foster trust and reduce privacy concerns (Aguirre et al., 2015; Martin et al., 2017), we assume that consumers are inclined to share this form of data.

Previous research also suggests that the specific type of data a firm seeks to collect influences consumer behavior (Dinev, Xu, Smith, and Hart, 2013; Mothersbaugh, Foxx, Beatty, and Wang, 2012). Consumers perceive a higher risk when the data requested becomes more sensitive. Those with heightened privacy concerns are less inclined to disclose sensitive information than those who prioritize less (Mothersbaugh et al., 2012). Therefore, we assume that privacy concerns affect consumers' willingness to disclose data, and consumers rank data types from less sensitive (less risky to share) to more sensitive.

Consumers expect value in return for sharing their data, considering it a form of “online currency” (Schumann et al., 2014, p. 69). We argue that the variation in utility for different personalized offerings influences consumers' preferences for sharing different data types. We thus propose that the costs related to consumer decision-making vary in response to different types of benefits. We anticipate that examining different personalization offerings will reveal 'currency' dynamics for different data types and shed light on the cost implications and benefits that influence consumer preferences.

4. Pilot study

Our pilot study uses a primary data collection method, including an online survey and preference measurement tasks. We conducted the study this year via the software *SoSci Survey* and analyzed the data using *R*.

4.1 Study design and measurement

The survey comprised three sections. First, the participants received an overview of the survey and guidance. The second part introduced four scenarios to the participants, each containing a series of preference options. The third section focused on ranking the data types and general benefits, privacy concerns (three-item scale by Dinev and Hart, 2006, measured by 5-point Likert), an attention check, a filter question, and demographics.

Specifically, we requested the participants select their preferred data type to share online with a hypothetical high-quality nutritional supplement producer in exchange for personalized offerings (benefits). We chose this industry due to its gender neutrality and high popularity. It ranks among the top ten categories for online content, aligning with resembling consumers' preferences for health and fitness advice (Spearman, 2023). We visually presented four personalized offerings, each representing a different scenario. The benefits included a personalized nutritional plan (digital product), product recommendations, an article on dietary supplements (personalized content), and a personalized price.

Moreover, we provided a consent form for each scenario where participants could indicate which data types they were willing to disclose (multiple selections). We presented the following data types based on our literature review (e.g., Davenport, 2023; Martin & Palmatier, 2020; Skiera et al., 2022; Plummer, 1974): socio-demographic information, behavioral data, purchase history, social media interactions, and data about activities, interests, and options (AIO). Furthermore, we incorporated an option for respondents to choose not to share any data, thereby giving them control over using their data.

4.2 Recruiting and sample characteristics

We employed convenient sampling from personal and university networks and recruited 185 participants for our survey. We excluded 55 respondents due to short completion times and failure on an attention check and filter question, resulting in a size of $N = 130$. The sample comprises 67.9% women ($n = 89$) and 30.5% men ($n = 40$). One participant was of a different gender. The respondents' ages range from 18 to 75.

4.3 Data analysis and results

We utilized privacy concern scales from existing literature and tested the multi-item scales on the appropriateness of dimension reduction (by factor analysis and Cronbach's alpha test). The result revealed, on average, moderate privacy concerns among the respondents ($M = 3.37$, $SD = .962$).

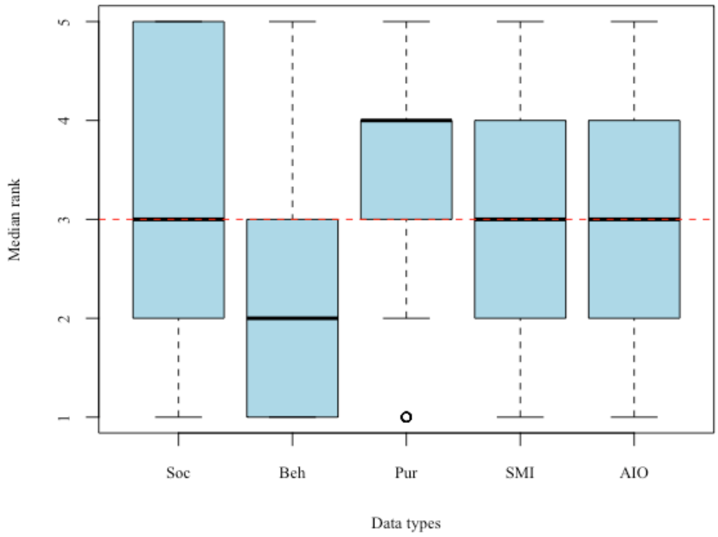

Figure 1. Boxplot rank of data types by median

The boxplot analysis (Figure 1) demonstrates dispersion in median ranks across the data types. The x-axis displays the data types, and the y-axis shows the ranking from one most sensitive to five least sensitive. The findings show that 'behavioral data (Beh)' exhibits the lowest median rank (2), and 'purchase history (Pur)' has a higher median rank (4). Notably, 'social media interactions (SMI)' and 'AIO' share the same median rank of three, suggesting a common perception among participants regarding their sensitiveness. The 'socio-demographic (Soc)' data displays a rank of three, yet it shows a broader interquartile range, indicating a greater diversity in participants' opinions. In addition, we conducted a Friedman's test to investigate potential variations in rankings assigned to data types. We aim to assess whether there are notable disparities in how the five items are ranked based on the participant's willingness to share them. We therefore chose Friedman's test for its suitability in analysis, as it deals with ranked data and ordinal variables. The results suggest the presence of significant differences in rankings ($\chi^2(df = 4) = 42.31$, $p < .001$) and imply that participants' rankings of the data types are not randomly distributed.

Additionally, we applied a Friedman's test to evaluate the ranking of personalized offerings in terms of their utility, as perceived by the participants. The test yields the presence of no significant differences in rankings ($\chi^2(df = 3) = 6.07$, $p = .11$). Despite this, the median ranks indicated the following hierarchy: nutritional plan and price both rank first with a median rank of two, followed by recommendation and content both ranking third with a median rank of three.

To understand the participants' attitudes toward data sharing across different types, we provide results from the survey in the context of our scenario in the following table.

Benefit		**SOC**	**BEH**	**PUR**	**SMI**	**AIO**	**None**
Nutritional plan	0	59	83	74	98	73	23
	1	71	47	56	32	57	
Recommendation	0	66	84	75	102	77	30
	1	64	46	55	28	53	
Content	0	72	78	79	100	75	30
	1	58	52	51	30	55	
Price	0	79	92	65	101	84	36
	1	51	38	65	29	46	

Note: 0 = not selected, 1 = selected, none = no sharing at all, adding to 0

Table 1. Frequencies: data types per benefit

The frequencies indicate that most participants are unwilling to share certain types of data in exchange for personalization. In particular, the mode for the data types per benefit is zero (not selected), except for the nutritional plan being one (selected) for socio-demographic data. Participants are most willing to share socio-demographic data and least willing to share social media interactions across all benefits. The 'None'-option indicates the number of participants unwilling to share data. On average, 22.8% of participants chose this option across all benefits.

5. Initial conclusion: implications, limitations, and future research

Our study aims to contribute to the understanding of the dynamics of consumer data valuation. We investigate how personalization affects consumers' choices to share various types of personal data and identify the most sensitive type (i.e., cost-intensive).

We extend research on privacy in marketing (e.g., Martin & Murphy, 2017) and online information disclosures (e.g., Schuman et al., 2014; Mothersbaugh et al., 2012) by focusing on zero-party data in the context of personalization.

Social exchange theory underscores the importance of assessing cost-benefit trade-offs. Drawing from our initial findings, we suggest that consumers are inclined to provide varying types of data depending on the different benefits presented. Firstly, our results suggest that individuals generally have moderate privacy concerns, which is in line with most previous studies (e.g., Martin & Murphy, 2017). Secondly, the findings show that consumers are most likely to share socio-demographic data when they receive personalization. In addition,

consumers are less willing to share information about social media interactions across all scenarios. This may be because socio-demographic data, like age, is categorical data, while social media interactions unveil individual preferences (Davenport, 2023).
Further, the lower rank assigned to behavioral data suggests that participants perceive this type as the most costly and sensitive. In contrast, the higher rank for purchase history implies lower perceived costs. Social media interactions and AIO share a similar rank, indicating a similar perception of these elements among the respondents. Socio-demographic data displayed a wider interquartile range, representing more diverse opinions.

The outcomes regarding the ranking of the personalized offers merely suggest a hint about hierarchy, indicating the perceived value of these offerings. Participants seem to assign a higher value to the nutritional plan. Also, most participants would provide data for this personalized digital product. This finding suggests that participants perceive greater utility in these offerings, possibly due to the tangible benefits they provide.

Our ongoing research provides preliminary implications for practitioners on how to deal with the third-party cookies phase-out and rebuild digital data-driven marketing strategies by utilizing zero-party data. Such an approach benefits consumers and firms by allowing consumers to choose their preferred type of data to share, empowering them with more control over privacy and personalized offerings while firms gain valuable data for personalization. We emphasize the importance of companies handling data-sharing practices with an understanding of consumer concerns. Acknowledging this can build trust and foster relationships (Bleier & Eisenbeis, 2015). Furthermore, firms prioritizing privacy practices may gain a long-term competitive advantage due to a better understanding of the market (Skiera et al., 2022).

While our pilot study provides preliminary results, it is crucial to acknowledge its limitations and suggest avenues for future research. Recognizing the subjective nature of participant rankings, contextual factors shaping perceptions of benefit should be investigated, potentially through longitudinal studies. Also, future research may delve into utility estimation and experiments to examine the relationship between personal data and the utility of personalization. Another research question of interest relates to whether individuals providing sensitive data express a higher appreciation for personalization than those sharing less sensitive information. Further, the simulated setting employed in this study may not fully capture the intuitive disclosure behavior as in a real online environment, highlighting the need for investigations using field data. Another limitation lies in the industry focus, suggesting the exploration of different firms or a between-subject design in future research.

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