Programmatic advertising in online retailing: consumer perceptions and future avenues

Received 30 June 2021
Revised 10 November 2021
3 March 2022
24 May 2022
Accepted 25 May 2022

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Abstract

Purpose – Digital advertising enables retailers to rely on large volumes of data on consumers and even leverage artificial intelligence (AI) to target consumers online with personalised and context-aware advertisements. One recent example of such advertisements is programmatic advertising (PA), which is facilitated by automatic bidding systems. Given that retailers are expected to increase their use of PA in the future, further insights on the pros and cons of PA are required. This paper aims to enhance the understanding of the implications of PA use for retailers.

Design/methodology/approach – A theoretical overview is conducted that compares PA to traditional advertising, with an empirical investigation into consumer attitudes towards PA (an online survey of 189 consumers using an experimental design) and a research agenda.

Findings – Consumer attitudes towards PA are positively related to attitudes towards the retailer. Further, perceived ad relevance is positively related to attitudes towards PA, which is moderated by (1) consumer perceptions of risks related to sharing their data with retailers online and (2) consumer perceptions of AI's positive potential. Surprisingly, the disclosed use of AI for PA does not significantly influence consumer attitudes towards PA.

Originality/value – This paper contributes to the literature on technology-enabled services by empirically demonstrating that ad relevance drives consumer attitudes towards PA. This paper further examines two contingencies: risk beliefs related to data (i.e. the source of PA) and perceptions of AI (i.e. the somewhat nebulous technology associated with PA) as beneficial. A research agenda illuminates central topics to guide future research on PA in retailing.

Keywords Programmatic advertising, Online retailing, Risk beliefs, Ad relevance, Artificial intelligence, Smart PLS

Paper type Research paper

This paper forms part of a special section "Evolutions and disruptions in retailing service through digital transformation", guest edited by Minjeong Kim and Jung-Hwan Kim.

Journal of Service Management
Vol. 34 No. 2, 2023
pp. 231-255
Emerald Publishing Limited
1757-5818
DOI 10.1108/JOSM-06-2021-0238

Introduction

Retailers increasingly engage in digital advertising as consumers migrate to online channels (Hennig-Thurau *et al.*, 2010; Larivière *et al.*, 2013). The use of programmatic advertising (PA) in this regard entails the ability to target consumers online in real time with personalised messages, with the help of automated purchasing of ads (Samuel *et al.*, 2021; White and Samuel, 2019). Hence, it combines ad personalisation and the automation of advertising placement. PA spending grew globally from 68.2 billion US dollars in 2017 to 155 billion US dollars in 2021 [1]. It is predicted that by 2025, 84% of all digital ad spending in the United States will be processed via PA [2].

PA is portrayed as an ideal method to market products online (Gonzalvez-Cabañas and Mochón, 2016), because it provides the potential to fit offered products to consumer needs and secure an instantaneous response from consumers (Hoban and Bucklin, 2015; Lee and Shin, 2020). It also offers efficiency and lower costs due to automation (Miklosik *et al.*, 2019) and enables reaching customers on the move through their smartphones. Overall, the better targeted and more attractive ads help online retailers reach consumers optimally and ultimately gain higher revenues, and the higher relevance and frictionless customer journeys are beneficial to customers as well (Malthouse *et al.*, 2019). However, there are several critical voices that warn that targeting in general may lead to suboptimal spending, where customers who are already loyal are targeted (Nelson-Field *et al.*, 2012; Sharp *et al.*, 2009). This implies that retailers need to go beyond current fan-based targeting methods (e.g. Facebook likers, email or mobile apps targeting extant customers) to more needs-based targeting, which is allowed by PA. However, with PA, retailers lose control over the context where the ad will be placed, because it may land on any online website.

Against this background, we identify and address an important research gap related to consumer reactions to PA. Despite the importance of PA for practitioners and its potential to reshape online retailing, this fast-developing phenomenon has received limited research attention (Samuel *et al.*, 2021). Extant research has focused on identifying the general benefits, characteristics and intricacies of PA (Araujo *et al.*, 2020; Helberger *et al.*, 2020) from a business-to-business perspective (i.e. concentrating on PA adopters and PA platforms; White and Samuel, 2019). On the other hand, studies on how consumers think and behave relative to PA are scarce. Little is known about consumers' attitudes towards PA (as an advertising practice) and their responses to retailers delivering highly personalised ads through big data and analytics (Samuel *et al.*, 2021). Nevertheless, such insights are needed particularly in the current times, as consumers tend to be more attentive to data-related risks overall and increasingly concerned with privacy online (Kabadayi *et al.*, 2019).

There are reasons to assume that advertisements generated through PA may evoke mixed responses in consumers (Samuel *et al.*, 2021). Drawing on rich findings from online advertising research (Liu-Thompkins, 2019) one reason could be the so-called personalisation paradox (Aguirre *et al.*, 2015). On the one hand, consumers may perceive PA ads as highly relevant due to their high degree of personalisation and context-embeddedness (due to the use of data which generates more fitting ads); on the other hand, the high relevance follows from the use of personal data to target the consumer with the ad. Ad relevance in PA should by default be high – but how will this relevance influence attitudes towards PA as a practice (as it indirectly signals that data are used) and the attitude towards the retailer? The current knowledge gap is a crucial drawback because a negative attitude towards the practice might also reflect on consumers' attitude towards the retailer.

This paper aims to enhance the understanding of the implications of PA use for retailers with the help of a theoretical overview that compares PA to traditional advertising, combined with an empirical investigation into consumer attitudes towards PA and a research agenda. In the empirical study, we focus on the personalisation tension of PA (Samuel *et al.*, 2021), which refers to how consumers react to retailers using increasingly sophisticated technologies to deliver them highly personalised ads online. The technology studied is artificial intelligence (AI), which is "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan and Haenlein, 2019, p. 17). The empirical findings show that perceived ad relevance is positively related to attitudes towards PA. This relationship is moderated by risk beliefs associated with online data disclosure and perceptions of AI as beneficial. When ad relevance is perceived as high, consumers' high risk beliefs are not problematic, but when ad relevance is perceived as low, high risk beliefs weaken the attitude towards PA. If consumers see AI as beneficial in general, it only strengthens the relationship between ad relevance and the attitude towards PA. Against our expectations, the disclosed use of AI for PA does not significantly influence consumer attitudes towards PA. Our findings suggest that consumers implicitly assume that AI is employed when they are informed that their data are used to bring them personalised ads.

We continue the paper with a discussion of online advertising and PA and the latter's complexities for online retailers. We then introduce the conceptual model and develop hypotheses on the general effect of ad relevance on attitudes towards PA, with two moderating effects, after which we present our empirical study, the analysis and results. The paper ends with a discussion and future research recommendations.

Conceptual background

Data and personalisation in online advertising

Advertising is facing changes in terms of the "constant addition of (new) media and formats, the evolution of (new) 'consumer' behaviors related to advertising, and a growing acknowledgment of extended effects of advertising" that imply changes for the future of advertising (Dahlén and Rosengren, 2016, p. 335). These developments are driven by the higher availability of increasingly detailed consumer data, which has enabled advertisers to reach the most interested consumers online (i.e. computational advertising) rather than, or in addition to, reaching large audiences offline (i.e. mass advertising; Malthouse *et al.*, 2018). Customer data may be first-party data, such as in the purchase of an item from the retailer. Data may also be sold; for example, a retailer may buy data from a housing brokerage firm to identify movers, in which case the data are second-party. Third-party data in turn refers to information that is collected by firms selling it professionally (Malthouse *et al.*, 2019), and this type of data (often in combination with first- and second-party data) is required to target customers online.

Using data based on consumers' online behaviour to show them highly relevant, i.e. personalised advertising is generally referred to as online behavioural advertising (see review in Boerman *et al.* (2017)). Personalization refers to "tailoring of message content and delivery based on data collection or covert observation of users, to increase the personal relevance of message" (Bang and Wojdynski, 2016, p. 868). Personalisation is one of the key topics in online advertising research and has been studied in relation to how different types of consumer data (e.g. consumer preferences, interests, and past and present behaviour) are used and processed to (re)target advertising (see Liu-Thompkins (2019) for a review). A typical example is online display advertising which takes the form of behavioural retargeting based on consumers' browsing behaviour (Bayer *et al.*, 2020). Traditionally, this was accomplished through browser cookie data, which can be first- or third-party data and may capture detailed information on the individual consumer (Palos-Sanchez *et al.*, 2019), including age, gender, location and preferences (Gonzalvez-Cabañas and Mochón, 2016).

Based on this data, advertisements are personalised, and higher degrees of personalisation imply indirect consumer benefits, e.g. more relevant and/or frictionless interactions. The benefits may also be direct, such as personalised information that helps the consumer adjust behaviour immediately (Malthouse *et al.*, 2019), e.g. geolocation data directing the consumer to the closest store. Kumar and Gupta (2016) proposed that high level of personalisation and the associated improved relevance would become more prevalent in future advertising and even required by customers.

PA and its personalisation tension

PA has emerged as "an automated big data system that allows organizations (predominantly retailers) to bid for the privilege to publish personalized online advertising in the right place, to the right people, at the right time" (Samuel *et al.*, 2021, p. 2). The PA system entails interaction between different groups of actors: PA adopters, PA platform developers and consumers (White and Samuel, 2019). PA aims to facilitate the generation of real-time ads that match the interests of individual consumers at the exact moment when they are most likely to make a purchase or click on an ad (Palos-Sanchez *et al.*, 2019; Yang *et al.*, 2017); this offers means for retailers to connect to their potential/existing customers during the purchasing journey.

Table 1 presents a comparison between traditional advertising and PA. The latter entails important implications for retailers and other marketers who aim to advertise their services and communicate with their customers.

Samuel *et al.* (2021) discuss three tensions stemming from the social, technological and economic complexity of the PA system: *personalisation* (i.e. the need for more data to deliver more personalised ads), *efficacy* (i.e. the need to adopt this novel approach to advertising without understanding its true impact) and *mechanisation* (i.e. the need for automation to reap speed and efficiency benefits). Henceforth, we focus on the personalisation tension, as it reflects increasing consumer concerns about the use of personal data and privacy (Cooper *et al.*, 2022; Rus-Arias *et al.*, 2021). The data collection and use may vary from simple cookie-based data collection and behavioural tracking to top players using big data-driven AI (e.g. machine learning and custom bidding algorithms) to increase an advertising campaign's success (Samuel *et al.*, 2021).

Reflecting the importance of personalisation tension, a survey by the World Federation of Advertisers [3] found that consumer privacy/sensitivity is a primary challenge in utilising PA data. Along similar lines, Palos-Sanchez *et al.* (2019) argue that PA may be invasive, because beyond the use of cookies and geolocation, PA employs algorithms to determine user interests to target them with relevant ads later, even while visiting pages unrelated to the original site where those interests were identified. Recently, Google announced that their Chrome browser will no longer support third-party cookies, which further emphasises fundamental changes in how online advertising deals with tracking and targeting consumers using data (Cooper *et al.*, 2022).

Hille *et al.* (2015) identify consumer privacy concerns as "consumers' apprehensions regarding how online companies collect and use their personal data" (p. 3). Consumers may experience concerns in three areas: firms collecting personal information, consumers' control over the use of personal data and consumer awareness of privacy practices (Malhotra *et al.*, 2004). If consumers become concerned about their data, they may refuse to disclose personal data online, provide fictitious data or even avoid websites they fear misuse their data (Bandyopadhyay, 2009).

Model and hypothesis development

To understand consumer perceptions of PA, we propose a model (Figure 1) with ad relevance as the main antecedent of customer attitudes to PA, with risk beliefs and perceptions of AI as beneficial as moderators, and attitude towards the retailer sponsoring the ad as the outcome. Next, we discuss the hypotheses.

We propose that ad relevance is positively correlated with consumer attitudes towards PA, because it is likely that consumers who find an ad relevant also attribute some of its usefulness to PA (as retailers are using their data to provide a highly personalised ad). In online advertising, perceived ad relevance is found to predict consumer responses (Hayes *et al.*, 2020; Kim and Huh, 2017; Liu-Thompkins, 2019). Supporting this hypothesis, Palos-

	Traditional advertising	Programmatic advertising (PA)	Key references
Target	Buying exposure through planning media choices	Fostering engagement through interaction planning	Araujo *et al.* (2020), Kumar and Gupta (2016)
Media buying process	Negotiated purchases	Programmatic purchases	Araujo *et al.* (2020), Li (2019), Malthouse *et al.* (2018)
Ecosystem	Advertisers, media agencies, ad agencies	Multiple actors and actions across several touch points, digital platforms playing a major role in facilitating exchanges	Helberger *et al.* (2020), Hennig-Thurau *et al.* (2010), Malthouse *et al.* (2019), Maslowska *et al.* (2016)
Contextual richness	Ad consumption context equalling channel choice	Situational aspects of the potential exposure, which are summarized as who, what, when, where, why and how	Araujo *et al.* (2020), Ketelaar *et al.* (2017), Malthouse *et al.* (2018)
Consumer coverage challenge	Efficiency – Reach and frequency (mass exposure at low cost per thousand impressions)	Precision – Increasingly precise coverage due to more precise attitudinal and behavioural information from tracking individuals' digital trace data across actions and touch points	Araujo *et al.* (2020), Fulgoni (2018), Klein *et al.* (2020), Kumar and Gupta (2016), Malthouse *et al.* (2018)
Consumer behavioural patterns underlying media planning	Accessibility due to similarity in behavioural patterns (e.g. large audience TV shows) Homogeneous audiences targeted through their media choices Observation of brand and media content	Fragmented consumer behaviour including ad avoidance Consumer participation and co-creation of brand and media content	Araujo *et al.* (2020), Baek and Morimoto (2012), Helberger *et al.* (2020), Liu-Thompkins *et al.* (2020)
Advertising content	Single-channel, one-way, brand-initiated, persuasive attempts Focus on ad content and format	Omnichannel, multi-way, partially user-initiated interactions throughout the consumer journey Focus on ability to deploy consumer data to target ad content and format	Araujo *et al.* (2020), Jahn and Kunz (2012), Klein *et al.* (2020), Li (2019)
Advertising efficiency measures	Proof of ad publication; reaching promised audience (size and composition); exposure and audience reach	Impression-based metrics Outcome-based metrics (e.g. brand, sales, return on investment [ROI]) potentially in combination with impression metrics	Araujo *et al.* (2020), Klein *et al.* (2020)
Challenges	Establishing a link between exposure and purchasing	Limited data access due to the platforms' "walled gardens", new ecosystem partners (e.g. hardware manufacturers) and privacy regulations making it difficult to estimate outcomes and personalize ads. Focus on short-term measures rather than long-term measures (e.g. experiences)	Araujo *et al.* (2020), Fulgoni (2018), Helberger *et al.* (2020), Yun *et al.* (2020)

Table 1.
Comparison of traditional and programmatic advertising

Sanchez *et al.* (2019) proposed a direct relationship between consumer attitudes and relevance/usefulness of PA. Moreover, research in service settings (i.e. recruiting) shows that when the use of personal data leads to a positive outcome, the perception of privacy invasion is lower than that for individuals not experiencing a positive outcome (Fusilier and Hoyer,

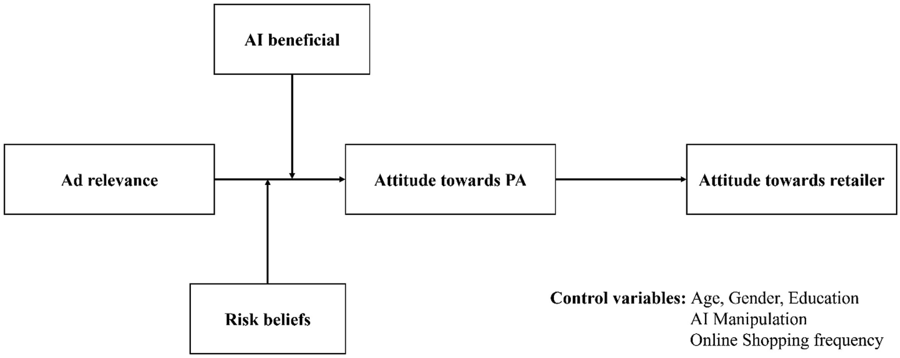

Figure 1.
Conceptual model

1980). This implies that PA is likely to be more positively viewed if relevance is high. Consequently, we propose that ad relevance leads to consumers' being more positively attuned towards PA:

H1. Ad relevance has a positive impact on consumer attitudes towards PA.

Although consumer attitudes towards PA may be higher if ad relevance is high, if risk beliefs are high, we propose that the attitude towards PA may decrease. In other words, we suggest that consumers' general risk beliefs related to sharing their data online (Malhotra *et al.*, 2004) moderate the influence of ad relevance on consumer attitude towards PA. This is because ad relevance in an online setting implies that the advertising retailer knows or appears to know about consumer preferences/needs. The riskier the consumers perceive handing over their information to be, the more likely it is that ad relevance will raise suspicions about PA. Earlier research has reported a negative correlation between risk beliefs and consumer intentions to share data with firms (Li *et al.*, 2011; Malhotra *et al.*, 2004), along with consumer privacy concerns leading even to ad avoidance (Ham, 2017; Jung, 2017). However, in the era of PA, much of the sharing may take place elsewhere, prior to the focal firm targeting the customer. Hence, we propose that risk beliefs about sharing data with online retailers moderate the relationship between ad relevance and consumer attitude towards PA:

H2a. Higher risk beliefs weaken the relationship between the ad relevance and consumer attitudes towards PA.

Moreover, we propose that the perceptions of AI as beneficial moderate the relationship between ad relevance and consumer attitudes towards PA. Studies (Liljander *et al.*, 2006; Parasuraman, 2000) have shown that consumers' positive view of a particular technology influences their attitudes towards using that technology. While studying customer intentions to adopt AI services, Flavián *et al.* (2021) found a positive impact of technology optimism on attitudes towards technology use. Whereas Flavián *et al.* (2021) and others studied general technological optimism, we investigate customer perceptions of AI as beneficial (Tussyadiah and Miller, 2019). We propose that if consumers perceive AI as beneficial, ad relevance has a heightened impact on attitude towards PA. This is due to ad relevance being viewed as a reflection of positive (AI) technology outcomes, leading to more positive attitude towards PA. Hence, we postulate the following:

H2b. Higher perceptions of AI as beneficial strengthen the relationship between the ad relevance and consumer attitudes towards PA.

Finally, consumer attitudes towards PA reflect consumer perceptions of the practices employed to show them ads (e.g. the extent to which it was acceptable that consumer data were used to show highly personalised ads) (Jin and Lutz, 2013). Although Schwaig *et al.* (2013) proposed that consumers' general attitudes towards information use practices lead to consumer intentions to block the use of their data, it is also likely that if consumers are positively attuned towards PA, it reflects positively on their attitude towards the retailer. Therefore, we hypothesise the following:

H3. Consumer attitudes towards PA positively impact their attitude towards the retailer.

As depicted in Figure 1, our model also includes several covariates (e.g. age, gender, education and shopping frequency).

Method

Study design

To collect data, we employed a 1X2 between-subject experimental design in which we manipulated the employment of AI for PA. Participants were instructed to imagine that they wanted to start their own business, an online store for plants, for which they were planning to set up their own website. Participants who indicated they could imagine themselves in this situation were then randomly assigned to one of two conditions: PA without AI and PA with AI. In both conditions, participants were asked to imagine casually browsing through their social media and coming across an advertisement for an online course on how to set up a website. Participants were then told that the online retailer who had sponsored the ad could show them such personalised advertising because it used *data* that had been collected about them online (PA without AI) or because it used *AI that analysed data* that had been collected on them online (PA with AI). Participants who indicated they did not carefully read the information were not allowed to continue answering the survey.

Our goal with this design was to simulate the PA's "best match" between a consumer in a specific context and a suitable ad (Yang *et al.*, 2017) by offering a situation in which the consumers would be directly interested in the ad (Samuel *et al.*, 2021). We kept the media and format of the ad as neutral as possible while mimicking the consumer context (i.e. consumers planning to set up their own website and seeing an ad for such services on social media). We also intentionally did not provide any additional information as to which data were collected and by whom, nor what kind of AI was employed or how. This is because we only wanted to sensitise participants to the general idea of PA without or with AI rather than its specifics which typically elude consumers. The online retailer employed in our study was fictitious to avoid any potential associations or relationships with existing online retailers.

We employed established scales (see Appendix 1) to measure the attitude towards the retailer (adapted from MacKenzie and Lutz (1989)), attitude towards the PA (adapted from Schwaig *et al.* (2013)), the ad relevance (adapted from Laczniak and Muehling (1993)), data risk beliefs (adapted from Malhotra *et al.* (2004)) and the extent to which respondents perceive AI as beneficial (adapted from Tussyadiah and Miller (2019)). Multiple screening questions (e.g. a CAPTCHA task to avoid bots) and attention checks were implemented in the survey to ensure high response quality (e.g. in a set of questions, one of the items was "*I am a robot from outer space*," and respondents who agreed to that statement were automatically excluded from the survey).

Participants

Participants were recruited through Amazon Mechanical Turk, an established data collection platform for social sciences (Goodman and Paolacci, 2017). Respondents residing in the

United States with an approval rating above 95% were asked to participate in the study for a \$1.00 compensation. Out of 200 respondents who requested compensation, 11 had to be rejected for entering an invalid completion code. Thus, our sample consisted of 189 respondents: 60% were male, 40% were under 35 years old and 56% held a bachelor's degree. Further, 94% of the respondents used social media at least once a day, and 61% shopped online at least once a week. Participants were assigned randomly to either the PA without AI ($n = 97$) or the PA with AI ($n = 92$) scenario.

Analysis and results

Manipulation checks

We asked the participants in both scenarios two manipulation check questions (each on a seven-point Likert scale anchored by "Strongly disagree" to "Strongly agree"). Independent samples t-tests show that there was no statistically significant difference between the two conditions on the data-focused manipulation check ("*ONLINE RETAILER uses my data to show me personalised advertising*"): $M_{\text{PA without AI}} = 5.73$ (SD = 0.92), $M_{\text{PA with AI}} = 5.66$ (SD = 1.14), $p = 0.59$. However, a statistically significant difference was found on the AI manipulation check ("*ONLINE RETAILER uses Artificial Intelligence (AI) to show me personalised advertising*"): $M_{\text{PA without AI}} = 4.88$ (SD = 1.52), $M_{\text{PA with AI}} = 5.90$ (SD = 1.18), $p < 0.01$. Interestingly, while the PA with AI manipulation functioned in the envisioned direction (i.e. respondents exposed to the PA with AI scenario had a significantly higher mean than respondents in the PA without AI scenario), the mean for respondents in the PA without AI condition is still high. This implies that although the scenario made no mention of AI, respondents have a higher-than-neutral perception of AI being used when data are employed for personalised advertising.

PLS-SEM results

We estimated our conceptual model (see Figure 1) in Smart PLS v3.3.3 using the consistent PLS algorithm with 5,000 bootstraps (complete bootstrapping, bias-corrected and accelerated bootstrap; Hair *et al.*, 2017). On each exogenous variable (i.e. attitude towards PA and towards the retailer), we controlled for the impact of our manipulation (0 = PA without AI condition; 1 = PA with AI condition), age (0 = Younger than 35; 1 = 35 and older), gender (0 = Female; 1 = Male), education (0 = Less than a Bachelor's degree; 1 = At least a Bachelor's degree) and shopping frequency (0 = Shops online weekly; 1 = Does not shop online weekly). Two models were estimated, a moderation-free model to test H1 and H3 (i.e. the direct effects) and a moderation model to test H2 (i.e. the interaction effects). Additional analyses were then carried out to explore the role of AI in PA.

Measurement model

As can be seen in Appendix 2, convergent validity is established since the outer loadings for each construct are above the threshold of 0.70, and the average variance extracted (AVE) is above the threshold of 0.50 (Hair *et al.*, 2017). Internal consistency reliability is also established since, for each construct, composite reliability and Cronbach's alpha values are above the threshold of 0.60 (Hair *et al.*, 2017). Finally, discriminant validity is established based on the heterotrait-monotrait (HTMT) criterion, as all HTMT ratios are lower than the 0.85 threshold, and none of the bias corrected confidence intervals for any relationship in the model includes the value 1 (Hair *et al.*, 2017). In sum, the measurement characteristics of the constructs employed in our analysis are adequate, so we can proceed to assessing the results of the structural model.

Structural model

The inner variance inflation factor (VIF) values for all combinations of endogenous and exogenous constructs are below the threshold of 5, indicating that collinearity among the predictor constructs is not a critical issue in the structural model (Hair *et al.*, 2017). The R^2 values of the endogenous latent variables are 0.73 in the moderation-free model and 0.81 in the moderation model for attitude towards the PA, and 0.80 in both models for attitude towards the retailer. To assess the predictive relevance of the model, we ran a blindfolding procedure with an omission distance [4] of 8 which yields Q^2 values considerably above zero: 0.49 in the moderation-free model and 0.53 in the moderation model for attitude towards PA, and 0.63 in both models for attitude towards the retailer. Appendix 3 provides an overview of R^2 and Q^2 and presents the f^2 and q^2 effect sizes for both models. While Hair *et al.* (2017) advise against the use of fit statistics in PLS-SEM, they condone a conservative approach to the standardised root mean square residual (SRMR) fit measure. The estimated model SRMR value in both our models is 0.04 below the 0.08 cut-off point, indicating good fit.

Hypotheses testing

To test our direct effect hypotheses, we consulted the bias corrected bootstrapped confidence interval for each path in the moderation-free model presented in Table 2: if 0 is not included in the confidence interval, the path coefficient is significant at 0.05 significance level. Results show a significant, positive path coefficient from ad relevance to attitude towards PA (0.44, [0.23, 0.62]) with a medium to strong effect ($f^2 = 0.29$) in support of H1. Attitude towards PA also shows a significant positive path coefficient (0.49, [0.27, 0.73]) to attitude towards the retailer with a medium to strong effect ($f^2 = 0.33$) in support of H3. The total effect of ad relevance on attitude towards the retailer (0.74, [0.56, 0.90]) is significant. Both the indirect path from ad relevance to attitude towards the retailer through attitude towards PA (0.22, [0.10, 0.36]) and the direct path from ad relevance to attitude towards the retailer (0.52, [0.31, 0.71]) are significant and positive. Thus, we find evidence for a complementary, partial mediation of ad relevance on consumer attitudes towards the retailer through their attitude towards PA. In terms of the control variables, there is a significant path coefficient from age to attitude towards retailer (i.e. older consumers are less positive about the retailer) and from online shopping frequency to attitude towards PA (i.e. consumers who shop less frequently online are more positive about the use of PA to show them ads).

To test the hypothesised interaction effects, we compute two interaction terms with the two-stage moderation procedure recommended for hypotheses testing in Smart PLS (Hair *et al.*, 2017). We then consult the bias corrected bootstrapped confidence interval for each path in the moderation model presented in Table 3. Both interactions, ad relevance × risk beliefs 0.28, (0.15, 0.43) and respectively ad relevance × AI beneficial 0.15, (0.07, 0.23), show positive, significant path coefficients on attitude towards PA (with a strong $f^2 = 0.36$ and respectively medium $f^2 = 0.16$ effect). These significant interaction effects are depicted in Figure 2. Mirroring H1, the simple slopes in Figure 2 show a positive relationship between ad relevance and attitude towards PA (i.e. the more relevant the ad, the more positive are the consumer attitudes towards the use of PA to show them that ad). However, the simple slopes in Figure 2b show that for lower general data risk perceptions, the relationship between ad relevance and attitude towards PA is not strengthened – in support of H2a. In contrast, the simple slopes in Figure 2a show that for higher levels of AI perceived as beneficial, the relationship between ad relevance and attitude towards PA is strengthened – in support of H2b. Appendix 4 provides an alternative representation of the interaction effects with bar charts.

Additional analysis

A dummy variable for the manipulation (0 = PA without AI condition; 1 = PA with AI condition) was used as a control variable in all models, but it did not yield a significant

Table 2.
Smart PLS moderation-free structural model

Path	Patch coefficient	t value	p value	Lower bound 95% CI	Upper bound 95% CI	Total effect	t value	p value	Lower bound 95% CI	Upper bound 95% CI
Ad relevance → Attitude towards PA	*0.44*	*4.43*	*0.00*	*0.23*	*0.62*	*0.44*	*4.43*	*0.00*	*0.23*	*0.62*
Risk beliefs → Attitude towards PA	*−0.16*	*2.85*	*0.00*	*−0.29*	*−0.06*	*−0.16*	*2.85*	*0.00*	*−0.29*	*−0.06*
AI Beneficial → Attitude towards PA	*0.36*	*3.50*	*0.00*	*0.16*	*0.56*	*0.36*	*3.50*	*0.00*	*0.16*	*0.56*
Ad relevance → Attitude towards retailer	*0.52*	*5.07*	*0.00*	*0.31*	*0.71*	*0.74*	*8.44*	*0.00*	*0.56*	*0.90*
Risk beliefs → Attitude towards retailer	−0.03	0.53	0.60	−0.12	0.07	*−0.11*	*2.34*	*0.02*	*−0.20*	*−0.02*
AI Beneficial → Attitude towards retailer	−0.13	1.28	0.20	−0.33	0.06	0.05	0.55	0.58	−0.13	0.22
Attitude towards PA → Attitude towards retailer	*0.49*	*4.15*	*0.00*	*0.27*	*0.73*	*0.49*	*4.15*	*0.00*	*0.27*	*0.73*
Age → Attitude towards PA	0.07	1.30	0.19	−0.03	0.16	0.07	1.30	0.19	−0.03	0.16
Age → Attitude towards retailer	*−0.10*	*2.16*	*0.03*	*−0.18*	*−0.01*	−0.06	1.41	0.16	−0.15	0.02
Gender → Attitude towards PA	0.05	0.94	0.35	−0.05	0.15	0.05	0.94	0.35	−0.05	0.15
Gender → Attitude towards retailer	−0.05	1.05	0.29	−0.13	0.04	−0.02	0.48	0.63	−0.12	0.07
Education → Attitude towards PA	0.09	1.63	0.10	−0.02	0.20	0.09	1.63	0.10	−0.02	0.20
Education → Attitude towards retailer	0.05	0.87	0.38	−0.07	0.16	0.10	1.55	0.12	−0.03	0.22
Online shopping frequency → Attitude towards PA	*0.15*	*3.26*	*0.00*	*0.06*	*0.24*	*0.15*	*3.26*	*0.00*	*0.06*	*0.24*
Online shopping frequency → Attitude towards retailer	−0.04	0.93	0.35	−0.12	0.04	0.04	0.83	0.41	−0.05	0.12
Manipulation → Attitude towards PA	0.03	0.59	0.56	−0.08	0.13	0.03	0.59	0.56	−0.08	0.13
Manipulation → Attitude towards retailer	−0.05	1.11	0.27	−0.13	0.04	−0.03	0.73	0.47	−0.12	0.06

Note(s): $n = 189$; PA = Programmatic Advertising; CI = Confidence Interval; NA = Not Applicable; Italicized paths are statistically significant at 0.05 significance level
CIs obtained through a complete, bias-corrected and accelerated bootstrap procedure with 5,000 samples
Dummy variables: Age (0 = Younger than 35; 1 = 35 and older), gender (0 = Female; 1 = Male), education (0 = Less than a Bachelor's degree; 1 = At least a Bachelor's degree), shopping frequency (0 = Shops online weekly; 1 = Does not shop online weekly) and manipulation (0 = PA without AI condition; 1 = PA with AI condition)

Table 3. Smart PLS moderation structural model

Path	Patch coefficient	t value	p value	Lower bound 95% CI	Upper bound 95% CI	Total effect	t value	p value	Lower bound 95% CI	Upper bound 95% CI
Ad relevance → Attitude towards PA	*0.41*	*3.64*	*0.00*	*0.16*	*0.61*	*0.41*	*3.67*	*0.00*	*0.16*	*0.60*
Risk beliefs → Attitude towards PA	*−0.29*	*4.13*	*0.00*	*−0.42*	*−0.15*	*−0.29*	*4.09*	*0.00*	*−0.42*	*−0.15*
AI beneficial → Attitude towards PA	*0.36*	*3.62*	*0.00*	*0.16*	*0.55*	*0.36*	*3.63*	*0.00*	*0.16*	*0.55*
Ad relevance × Risk beliefs → Attitude towards PA	*0.28*	*3.85*	*0.00*	*0.15*	*0.43*	*0.28*	*3.93*	*0.00*	*0.16*	*0.43*
Ad relevance × AI beneficial → Attitude towards PA	*0.15*	*3.88*	*0.00*	*0.07*	*0.23*	*0.15*	*3.78*	*0.00*	*0.07*	*0.23*
Ad relevance → Attitude towards retailer	*0.52*	*5.12*	*0.00*	*0.30*	*0.71*	*0.72*	*9.00*	*0.00*	*0.55*	*0.87*
Risk beliefs → Attitude towards retailer	−0.03	0.54	0.59	−0.12	0.07	*−0.17*	*3.26*	*0.00*	*−0.27*	*−0.07*
AI beneficial → Attitude towards retailer	−0.13	1.32	0.19	−0.32	0.06	0.05	0.60	0.55	−0.11	0.20
Attitude towards PA → Attitude towards retailer	*0.49*	*4.16*	*0.00*	*0.27*	*0.73*	*0.49*	*4.26*	*0.00*	*0.27*	*0.71*
Ad relevance × AI → Attitude towards retailer	NA	NA	NA	NA	NA	*0.08*	*2.72*	*0.01*	*0.03*	*0.14*
Ad relevance × Risk → Attitude towards retailer	NA	NA	NA	NA	NA	*0.14*	*2.96*	*0.00*	*0.06*	*0.24*
Age → Attitude towards PA	0.07	1.44	0.15	−0.03	0.17	0.07	1.44	0.15	−0.02	0.16
Age → Attitude towards retailer	*−0.10*	*2.11*	*0.04*	*−0.18*	*−0.01*	−0.06	1.42	0.16	−0.15	0.02
Gender → Attitude towards PA	0.05	1.06	0.29	−0.04	0.16	0.05	1.06	0.29	−0.05	0.15
Gender → Attitude towards retailer	−0.05	1.06	0.29	−0.13	0.04	−0.02	0.46	0.65	−0.11	0.07
Education → Attitude towards PA	0.09	1.62	0.11	−0.02	0.20	0.09	1.64	0.10	−0.01	0.20
Education → Attitude towards retailer	0.05	0.88	0.38	−0.06	0.16	0.09	1.58	0.11	−0.02	0.21
Online shopping frequency → Attitude towards PA	*0.12*	*2.47*	*0.01*	*0.03*	*0.21*	*0.12*	*2.45*	*0.01*	*0.02*	*0.21*
Online shopping frequency → Attitude towards retailer	−0.04	0.91	0.36	−0.12	0.04	0.02	0.41	0.68	−0.07	0.10
Manipulation → Attitude towards PA	0.03	0.57	0.57	−0.07	0.12	0.03	0.58	0.57	−0.07	0.12
Manipulation → Attitude towards retailer	−0.05	1.10	0.27	−0.13	0.04	−0.03	0.76	0.45	−0.13	0.05

Note(s): $n = 189$; PA = Programmatic Advertising; CI = Confidence Interval; NA = Not Applicable; Italicized paths are statistically significant at 0.05 significance level
CIs obtained through a complete, bias-corrected and accelerated bootstrap procedure with 5,000 samples
Dummy variables: Age (0 = Younger than 35; 1 = 35 and older), gender (0 = Female; 1 = Male), education (0 = Less than a Bachelor's degree; 1 = At least a Bachelor's degree), shopping frequency (0 = Shops online weekly; 1 = Does not shop online weekly) and manipulation (0 = PA without AI condition; 1 = PA with AI condition)

A. Ad relevance x Risk beliefs → Attitude towards PA

B. Ad relevance x AI beneficial → Attitude towards PA

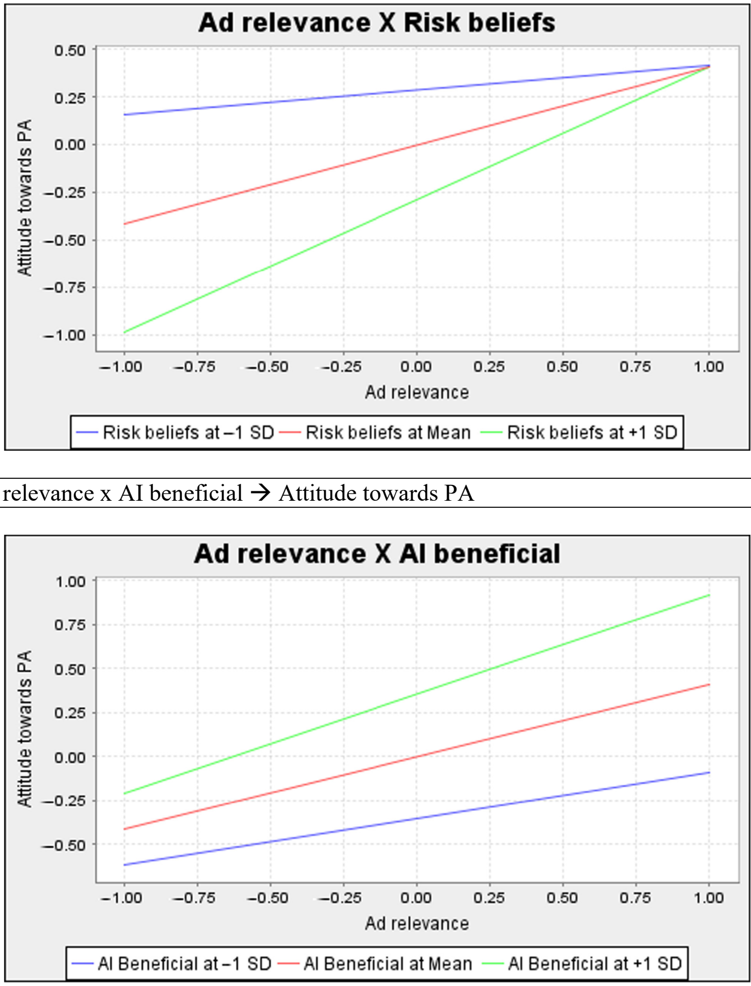

Figure 2.
Simple slope analysis visualizations of interaction effects

Note(s): SD = Standard deviation;
In each visualization, the middle line represents the relationship between ad relevance and attitude towards PA for an average level of each moderator and the other two lines represent the relationship at higher (i.e., mean +1 SD) or lower (i.e., mean – 1SD) levels of each moderator

influence on any of the outcome variables. Nevertheless, we conducted some additional analyses to test differences in the entire model for two subsamples: participants exposed to PA without and respectively with AI. This type of comparison is possible through multi-group analysis in Smart PLS (PLS MGA), a non-parametric significance test for the difference of group-specific results that builds on bootstrapping results (Hair *et al.*, 2017). The results show a statistically significant difference ($p < 0.01$) in the path coefficients for the relationship between attitude towards PA and attitude towards the retailer. Specifically, the path coefficient for this relationship in the moderation model estimated on the sub-sample exposed to PA without AI ($n = 97$) is significantly higher than in the subsample exposed to PA with AI ($n = 92$), while both paths are significant in their respective models.

Discussion

Our study examines PA, a way for retailers to reach potential consumers online with the efficient automised ad placement based on bidding (Samuel *et al.*, 2021). To date, little is known about consumer attitudes towards PA and towards the retailers who employ PA. Hence, our results complement the largely conceptual field of PA research with a predominant business-to-business perspective (Araujo *et al.*, 2020; Helberger *et al.*, 2020; Samuel *et al.*, 2021). In this experimental study, we exposed participants to a personalised online ad, creating a scenario emulating PA from a consumer's point of view. Our findings corroborate earlier studies (e.g. Kim and Huh, 2017) and show that if consumers find an online ad relevant, they are more likely to have a positive attitude towards PA having been used. It means that the relevance of an ad justifies the use of consumer data. In our study, ad relevance not only had an influence on the attitude towards PA but also had a direct influence on the attitude towards the retailer, supporting the important role of relevance that has been reported in other online advertising contexts (Kim and Huh, 2017; Hayes *et al.*, 2020).

We further examined two contingencies, one related to the source of the PA (i.e. consumer's general risk beliefs about sharing data with retailers online) and the second related to a novel-yet-nebulous technology often associated with PA (i.e. consumer general perceptions of AI as beneficial). Our results show that risk beliefs moderate the relationship between ad relevance and attitudes towards PA. Particularly, the relationship between ad relevance and attitudes towards PA is weakest when risk beliefs are high and ad relevance is low. Our results also show that perceptions of AI as beneficial moderate the relationship between ad relevance and attitudes towards PA. Specifically, the more consumers perceive AI as beneficial, the stronger is the relationship between ad relevance and attitudes towards PA. These findings are in line with results from previous research (Flavián *et al.*, 2021; Liljander *et al.*, 2006; Parasuraman, 2000) suggesting that consumers' positive views on a particular technology influence their attitudes towards using that technology. However, whereas earlier research has investigated consumers' own technology use, we demonstrate that these findings extend to retailers' use of technology (in terms of data being used to create PA) and reflect positively on consumer attitudes towards the retailer.

Consumers seem to assume that AI is used to personalise ads, not differentiating between data use and AI. Surprisingly, the explicit use of AI in PA did not have detrimental effects on consumer attitudes towards PA or towards the retailer, which is an optimistic finding for retailers aspiring to increase their use of AI in online advertising. Furthermore, the results suggest a significantly weaker impact of consumer attitudes towards PA on attitudes towards the retailer when AI is explicitly mentioned compared to when it is not. It may be that AI use awakes some concerns about the retailer behind the ad. This result hints at the need to study in more depth consumer perceptions of AI being employed for PA. Our manipulation checks show that when consumers are made aware that their data are used to show them ads (without an explicit mention of AI), they still have a higher-than-neutral perception that AI is involved. The level of transparency (informing participants in our scenarios that the highly personalised ad was created based on their personal data) may explain this finding. Nevertheless, that consumers think that AI is involved somewhat by default is unexpected since most retailers are just starting to explore using AI for PA.

Managerial implications

Since PA requires third-party data or use of data by third parties, it can be argued that consumer attitudes towards PA can potentially reflect negatively on attitudes towards the ad and the retailer. However, according to our findings, if retailers succeed in personalisation by showing relevant ads, then consumers will most likely have a positive attitude towards the retailer. Still, retailers need to respect consumers' need to protect their data, which requires considerations of the kinds of data to be collected, the purposes the data are used for, and with whom the data are shared (Martin, 2016); this will ensure that consumers are willing to share their data in the future (White and Samuel, 2019). If retailers wish to cultivate positive consumer attitudes by employing PA, apart from ensuring that ad relevance for the consumers is on a high level, they need to educate consumers about the general benefits of employing AI as well as monitor and address consumer-perceived risk related to data sharing.

Regarding the disadvantages of PA, whereas it aims to be temporally precise (identifying the customer at the point of purchase) at low cost, the advertiser loses control of the context in which the ad is placed. Especially for sensitive products (e.g. related to sexuality or health) or for retailers promoting a strong ideology or being at the high-end scale, choosing appropriate media may be a wiser option than letting bidding systems place the ads haphazardly online. This may be particularly prevalent in the current turbulent times, such as during a pandemic or political uprising, where potential landing pages may be detrimental to the retailers' brand image. Moreover, retailers may need to monitor how the new customers attracted with the help of PA score in the long run in terms of profitability and how existing customers perceive PA.

Avenues for future research

Starting from our findings on ad relevance, data concerns and AI perceptions, and expanding with the recent literature on online advertising (see Table 1 in the conceptual background), we divide the research agenda into two major themes for the future of service retailing and PA use. These themes are briefly discussed below, with research questions suggested in Table 4.

Theme 1: Consumers in the era of PA and AI

There are multiple interesting avenues for future research, ranging from consumer privacy concerns to other consumer responses. For example, ad relevance (one of the main drivers of consumer attitudes towards PA in our study) is seen as an outcome of data use and personalisation (Aguirre *et al.*, 2015), and some research has investigated ad relevance as an antecedent to privacy concerns and ad avoidance (Jung, 2017), which may be particularly relevant in case of PA. Such negative consequences of PA offer one interesting avenue for further research along with more positive outcomes that PA may have. Furthermore, it would be useful to determine what kind of self-defence (e.g. throw-away profiles) or even sabotage (e.g. providing false data) methods consumers may engage in response to PA. Other interesting positive outcomes of PA, such as omnichannel loyalty and purchase behaviours, should be likewise studied.

While the use of AI in online retailing is likely to grow, there is currently little research into how consumers perceive retailers' investment in AI (e.g. in relation to data, algorithms, etc.) and to what extent they understand and accept its use (Puntoni *et al.*, 2021). In our study, we examined the moderating role of perceptions of AI as beneficial, and we found a positive effect on attitudes towards PA. However, we also found that consumers are still somewhat confused about AI and that the border between AI and data remains blurry. An interesting area for future study is thereby how the (perceptions of) employment of such technologies in advertising influence consumers and in turn impact retailers.

Underlying the developments in advertising is datafication, which refers to "the collection, databasing, quantification and analysis of information, and the uses of these data as resources for knowledge production, service optimization, and economic value-generation"

Table 4. Future research agenda

Themes	Research questions
*Consumers in the era of PA**	
Consumer behaviour	What benefits/sacrifices do consumer experience with PA? What factors influence these benefits/sacrifices? What is the impact of PA on consumer behaviour, such as buying, loyalty, trust, engagement, word of mouth (WOM), user-generated content (UGC), or satisfaction? What emotions (e.g. happiness, disgust, surprise, anger, shame, or excitement) does PA evoke among consumers? Are there mixed (ambivalent) emotions? How do the emotions affect the behaviour? How do cognitions, emotions, and behaviours interact compared to traditional ads? Under what circumstances will consumers respond favourably to PA in the long term? When do consumers perceive problematic clashes between the context (e.g. website or mobile app content) and PA? What kinds of different "forced exposures" are there? What are their significance and consumer reactions? Are there different consumer reactions to the use of first-, second-, and third-party data use for PA? Are there differences between generations/cultures and their attitudes towards PA? What can explain the differences? What kinds of PA do the consumers find annoying/intrusive? What kinds of PA make the consumers feel vulnerable? When do they feel forced exposure? Does PA frequency make a difference? What is the relative impact and significance in different situations of multiple advertisement forms? How will consumers react to PA in new technologies and platforms such as virtual reality (VR), augmented reality (AR), wearable technologies, and robots?
Consumer counter-behaviour to PA	Will consumers increase their ad blocker use if/when PA increases? Under what conditions will they do so? What kinds of self-defence processing and negative evaluations can consumers engage in? What kinds of new sabotage/coping methods could be possible in addition to providing false data or creating multiple online user profiles? When and/or what types of consumers try to sabotage PA? What are the reasons for doing so?
Meaning of AI	How do consumers understand AI, and what is their extent of knowledge of it? Is AI as cryptic for consumers to understand as is typically assumed? What do consumers think can be done with AI today and in the future? In what ways do consumers perceive AI and related technologies to be destructive/harmful? What types of environmental impacts do consumers associate with AI? What impact do beliefs about AI have on their reactions to PA and behaviour in general? When do consumers perceive that the personalisation is problematic? E.g. when is online usage public, and are there ways that AI can detect this? Do consumers understand that personal information that they volunteered to give/gave consent to can be turned into new information about them (e.g. with AI) that they have no control over?
Increasing data collection and use in society	Are people willing to proactively trade or sell their personal data to gain benefits/products? To whom? Under what circumstances? In what situations and why do they volunteer/refuse to give data? What factors and incidents have significant impact on the attitudes? What is the attitude among consumers and citizens towards the increasing amount of data being collected about and from them? In what situations are they exceptionally positive/exceptionally negative? How do consumers and citizens feel about datafication? What emotions does it evoke? Do they have fears? How do the attitudes change over time as datafication increases (longitudinal approach)? How do consumers and citizens think about data being stolen, bought, hacked, or manipulated? What are the effects on their behaviour as a result? How familiar are consumers and citizens with their rights and how data about them is collected, stored, and used?

(*continued*)

Table 4.

Themes	Research questions
Privacy and risk beliefs	In what ways do consumers (try to) protect their personal information by restricting or limiting others from accessing it? What do consumers do when their privacy has been violated?
	What makes consumers suspect misuse of their data? What kind of websites do consumers suspect misuse their data?
	How do consumers perceive the "personalisation-privacy paradox" in different situations?
	In what situations and for what services do consumers care exceptionally more/less about privacy?
	How do consumers think about the processing of data about them to generate new information and knowledge?
	What data types (e.g. personal information, behavioural data, location data) in general and subtypes (e.g. sexual orientation, race, health data) do consumers feel comfortable giving?
	How do consumers feel about predictions about them that are made using AI predictive analysis? When are they more/less comfortable with them?
AI-driven advertising and PA for retailers	
Strategies	What is the suitability of PA for different service types and for different products?
	How does PA/AI use interact with different brand personalities (i.e. are there retailer brands that benefit more/less from PA/AI use)?
	How can PA/AI be aligned with brand strategies?
	What are the alternative methods of PA in specific and personalisation in general if legislation prevents retailers from collecting data across channels?
	What are the consequences of the implementation of the General Data Protection Regulation (GDPR)?
	What kind of potential do new technologies and platform such as VR, AR, wearable technologies, and robots offer in terms of PA and AI use?
Impacts	How does the use of PA affect retailer–customer relationships in the short/long term?
	How does customer trust affect the efficiency and effectiveness of PA in retailing?
	How does retailer trust interact with PA ad relevance? In particular, does consumer trust towards the retailer ameliorate the possibly negative impacts of ad relevance for consumers with high data risk profile?
	What new measures should/could advertisers use to determine the impact of PA?
	Under what circumstances can it be a competitive advantage for retailers to not use data and/or allow consumers to remain anonymous?
Ethical issues	How should retailers consider vulnerable consumers (e.g. children, elderly) when advertising online?
	When can and should consumer data be purchased from, sold to, or distributed among other actors?
	How can policy, regulation, and legislation be updated to cover consumer privacy and ethical issues when AI is used in digital advertising?
	How are offerings related to sensitive matters (e.g. sexuality, religion, health) conveyed in a manner that is unobtrusive?
	What is the role of data and privacy policies, such as consent and GDPR, and how can retailers ensure ethical PA/AI use?
	Who owns and can monetise the new information generated with AI? How can retailers deploy it without acting unethically?
Ecosystem development	What kind of ecosystems of companies and platforms emerge for future AI-driven advertising? What media trading, content creation, business intelligence, data brokers, analytics, and data management platforms are needed?
	How can retailers deploy systems utilising unstructured data that are increasingly available online (e.g. user-generated content related to the retailer) to predict consumer behavioural trends?
	How can retailers build an ecosystem to track and address consumer preferences and behaviour (e.g. through aps, payment systems)?
	How can retailers solve the struggles between short- and long-term goals for different ecosystem partners?
	How are positive financial outcomes shared among ecosystem partners (e.g. models from data sales to provisions)?
	How can retailers avoid a loss of power to walled gardens and emerging (large) ecosystem actors who own customer data?

Note(s): *Although we here refer to PA, we propose similar questions are relevant for all types of new advertising techniques and/or use of customer data

(Flensburg and Lomborg, 2021, p. 1). Datafication raises several important questions regarding consumers' and citizens' reactions to use of data by service providers. Data serve as the fuel for PA, and in our research, we examined one related factor: the role of data risk beliefs. Future research can examine other consumer attitudes to different types of data being collected and consider how general attitudes towards datafication evolve (e.g. through longitudinal field studies).

Intelligent advertising ("consumer-centered, data-driven, and algorithm-mediated brand communication" (Li, 2019, p. 333)) may be the next step of digital advertising and by inclusion PA. Intelligent advertising brings along a new type of personalisation by prescribing user needs and wants in real-time context to recommend offerings with the help of AI technologies such as machine learning and voice automation. Consumer attitudes towards these prescriptive techniques offer interesting research avenues.

In this regard, one particularly relevant field to be studied is the linkage between AI and sustainability (see, e.g. the items used to assess AI as beneficial in our study). One question could be: will consumers balance the positive and negative consequences of AI as a constructive force that helps solve big-scale problems, such as global warming, but also as a potential energy-consuming factor that causes problems? Simultaneously, the use of digital services requires large quantities of energy due to data storage, transfer and use. Hence, an equally relevant area for the benefit of retailers is the environmental impact of online advertising, including PA (e.g. Pärssinen *et al.*, 2018), because future retailers urgently need to understand and assess energy consumption and CO_2 emissions of their online activities. Simplifying the production systems, lowering the number of layers between creating and delivering ads, and reducing the data load by shortening and simplifying them would be some options for how to reduce the CO_2 footprint of online advertising.

Theme 2: AI-driven advertising and PA for retailers

A pervasive theme is the impact that new advertising strategies have on retailers. Although targeting customers with the help of PA and AI is attractive due to cost-effectiveness, it may lead to negative outcomes. On the one hand, precision may entail a drastic drop in reach (Fulgoni, 2018; Nelson-Field *et al.*, 2012). If only current customers receive the brand messages, the targeting may lead to stagnation of the customer base and reduce sales (Nelson-Field *et al.*, 2012). On the other hand, microtargeting that increasingly predicts personal needs and wants entails ethical challenges, both in restricting customer choice and in terms of (over-)collection, use and potential sharing of data.

In the last decades, advertising has expanded from a controllable ecosystem with stable, selected partners to one where parties are brought together through automation and, with large user numbers and amounts of data, hold considerable power. This raises several questions regarding the political, social and practical influence of the data giants (e.g. Facebook/Meta, Google/Alphabet) in shaping the ecosystems as well as their obligations and rights vis-à-vis other, sometimes small, and possibly local, players, such as small and medium-sized retailers. In our research, we intentionally did not provide any additional information as to what data were collected and by whom (i.e. the retailer, a third party, etc.). Ethical questions about how consumer data are monetised arise (Breidbach and Maglio, 2020), and further research into how consumers react to trusted service providers potentially selling and buying their data is needed.

Development in advertising and technology is inevitable, and service retailers, similar to all marketers, must stay on track with technological advancements, the opportunities these offer, and other marketing strategies and tactics.

Notes

1. https://www.statista.com/statistics/275806/programmatic-spending-worldwide/

2. https://www.statista.com/statistics/676585/programmatic-ad-spend-countries/
3. https://wfanet.org/
4. An omission distance between 5 and 10 is recommended with the requirement that the number of observations used in the model estimation (189 in our case) divided by the omission distance (8 in our case) is not an integer (Hair *et al.*, 2017).

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Appendix 1

Construct	Scale adapted from	Items
Attitude towards the retailer	MacKenzie and Lutz (1989)	What are your overall feelings towards "RETAILER", the company that paid for you to see the advertisement? • ARE1: 1 = Bad – 7 = Good • ARE2: 1 = Unpleasant – 7 = Pleasant • ARE3: 1 = Unfavourable – 7 = Favourable
Attitude towards the PA	Schwaig *et al.* (2013)	To what extent do you disagree or agree with the following statements about how "ONLINE RETAILER" used your data? *(1 = Strongly disagree – 7 = Strongly agree)* • APA1: It was acceptable for ONLINE RETAILER to use my data • APA2: It was necessary for ONLINE RETAILER to use my data • APA3: I feel comfortable with my data being used in this way by ONLINE RETAILER
Ad relevance	Laczniak and Muehling (1993)	When I saw the personalized advertisement, I felt it . . . *(1 = Strongly disagree – 7 = Strongly agree)* • AREL1: . . . is important to me • AREL2: . . . is meaningful to me • AREL3: . . . is "for me." • AREL4: . . . is worth remembering • AREL5: . . . is of value to me • AREL6: . . . is useful to me • AREL7: . . . is worth paying attention to • AREL8: . . . is interesting to me • AREL9: . . . gives me new ideas
Risk beliefs	Malhotra *et al.* (2004)	To what extent do you disagree or agree with the following statements about giving your data to online companies? *(1 = Strongly disagree – 7 = Strongly agree)* • RBEL1: In general, it is risky to give my data to online companies • RBEL2: There is too much uncertainty associated with giving my data to online firms • RBEL3: Providing online firms with my data would involve many unexpected problems
AI beneficial	Tussyadiah and Miller (2019)	To what extent do you disagree or agree with the following general statements about Artificial intelligence (AI)? *(1 = Strongly disagree – 7 = Strongly agree)* • AIBEN1: AI makes better use of energy and natural resources • AIBEN2: AI has a positive impact on our environment • AIBEN3: AI brings greater social equality • AIBEN4: AI offers companionship

Table A1.
Constructs, scales and items

Appendix 2

Latent variable	Indicators	Loadings	AVE	CR	Alpha	1	2	3	4	5
1. Attitude towards the retailer	ARE1	0.93	0.84	0.94	0.94					
	ARE2	0.91								
	ARE3	0.91								
2. Attitude towards the PA	APA1	0.90	0.72	0.89	0.88	*0.83*				
	APA2	0.77								
	APA3	0.88								
3. Ad relevance	AREL1	0.86	0.67	0.95	0.95	*0.84*	*0.79*			
	AREL2	0.78								
	AREL3	0.85								
	AREL4	0.72								
	AREL5	0.85								
	AREL6	0.91								
	AREL7	0.80								
	AREL8	0.74								
	AREL9	0.85								
4. Risk beliefs	RBEL1	0.90	0.73	0.89	0.88	*0.38*	*0.39*	*0.33*		
	RBEL2	0.94								
	RBEL3	0.70								
5. AI beneficial	AIBEN1	0.73	0.62	0.87	0.87	*0.66*	*0.74*	*0.74*	*0.24*	
	AIBEN2	0.75								
	AIBEN3	0.83								
	AIBEN4	0.83								

Note(s): $n = 189$
Convergent validity
- Outer loadings for each indicator of each latent variable are equal to or higher than the 0.70 threshold
- AVE = Average variance extracted; All values are higher than the 0.50 threshold

Internal consistency reliability
- CR = Composite reliability. All values are within the 0.60 – 0.95 thresholds
- Alpha = Cronbach's alpha; All values are higher than the 0.60 threshold

Discriminant validity
- Italicized numbers indicate the Heterotrait – Monotrait (HTMT) Ratios; All values are under the 0.85 threshold
- Bootstrapped (5,000 samples) bias corrected HTMT confidence intervals do not include 1

Table A2. Construct reliability and validity, discriminant validity

Appendix 3

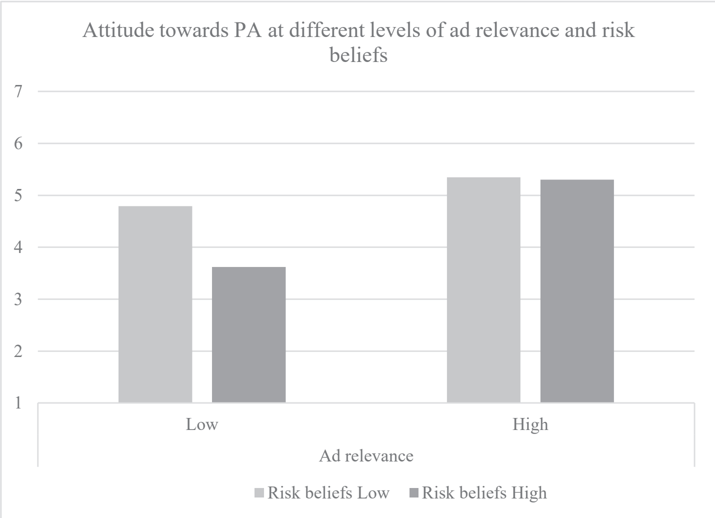
	Moderation-free model				Moderation model			
	Attitude towards PA		Attitude towards retailer		Attitude towards PA		Attitude towards retailer	
	R^2	Q^2	R^2	Q^2	R^2	Q^2	R^2	Q^2
	0.73	0.49	0.80	0.63	0.81	0.53	0.80	0.63
Effect size	f^2	q^2	f^2	q^2	f^2	q^2	f^2	q^2
Ad relevance	0.29	0.15	0.42	0.23	0.29	0.25	0.42	0.23
AI beneficial	0.20	0.07	0.03	0.00	0.28	0.12	0.03	0.00
Risk beliefs	0.08	0.03	0.00	0.01	0.31	0.11	0.00	0.00
Attitude towards PA	NA	NA	0.33	0.12	NA	NA	0.33	0.12
Ad Relevance × AI	NA	NA	NA	NA	0.16	NA	NA	NA
Ad Relevance × Risk	NA	NA	NA	NA	0.36	NA	NA	NA

Note(s): NA = Not applicable
f^2 effect size assesses an exogenous construct's contribution to a latent variable's R^2 value
q^2 effect size assesses an exogenous construct's contribution to an endogenous variable's Q^2 value
0.02, 0.15 and 0.35 indicate a small, medium, and respectively large effect (Hair *et al.*, 2017)

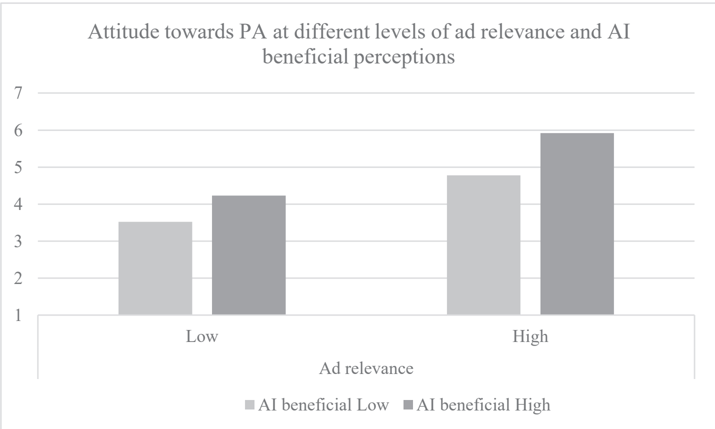
Table A3.
Predictive power of moderation free and moderation models

Appendix 4

Ad relevance x Risk beliefs → Attitude towards PA



Ad relevance x AI beneficial → Attitude towards PA



Note(s): Low denotes Mean – 1 standard deviation; High denotes mean + 1 standard deviation

Figure A1. Alternative visualizations of interaction effects