Programmatic Advertising in the Age of AI:
A Conceptual Overview and Strategic Recommendations

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Abstract

Artificial intelligence (AI) is revolutionizing the field of programmatic digital marketing. This article provides a forward-looking perspective on AI in advertising and offers a conceptual framework for developing effective marketing strategies. We explore key developments in the industry: the progression from personalized to contextual targeting, and the increased reliance on AI-based automation. Additionally, the article identifies three critical factors – results, resources, and rectitude – that influence the choice of strategies for online advertisers. Our findings suggest that while AI might multiply the effectiveness of programmatic advertising campaigns, it comes with important tradeoffs that must be taken into account. By synthesizing literature from digital advertising, computer science, and media studies, we offer an improved understanding of the evolving programmatic advertising ecosystem and distill this into practical advice for advertisers.

Keywords: programmatic advertising, contextual targeting, personalized targeting, artificial intelligence

1. Introduction

The increased adoption of artificial intelligence (AI) holds great promise for programmatic advertising but entails risks and trade-offs not yet widely understood. In this rapidly changing environment, two trends obscure the broader implications for industry: the rapid pace of technological development, and the pressure to move away from privacy-intrusive targeting practices. Strategic clarity and practical guidance are urgently needed. The purpose of this paper is to meet this need.

In late 2022, OpenAI made headlines with the introduction of their language model ChatGPT (OpenAI, 2022) chatbot that captured the public's imagination and rapidly amassed a global user base (The Economist, 2023). ChatGPT represented a new generation of AI systems, which today includes diverse services such as DALL·E 3 (Betker et al., 2023) and Midjourney (Salkowitz, 2022) for image generation, Sora (Brooks et al., 2024) and Lumiere (Bar-Tal et al., 2024) for creating videos, and Gemini (Gemini Team et al., 2023) and Copilot (Spataro, 2023) which enable interactive conversations in a manner akin to ChatGPT. Like many of their technological predecessors, these AI systems were quick to find applications in advertising (Gołąb-Andrzejak, 2023; Li et al., 2023).

However, forms of AI have been a cornerstone of digital marketing for many years. This is particularly true for programmatic advertising, which involves the automated auctioning of digital ad space and distribution of ads (Alaimo & Kallinikos, 2018). In recent years, this form of marketing has undergone explosive growth: global programmatic advertising spending reached $595 billion in 2024, up from $178 billion in 2017, and is projected to reach $779 billion by 2028 (Statista, 2024a). It is estimated that between 82% (Statista, 2024b) and 91% (Byrd, 2023) of digital display ads are now traded programmatically. As the influence of AI continues to expand, programmatic advertising is poised to achieve near-total dominance in the online marketplace in the near future.

While programmatic advertising continues to grow, advertisers face a complex landscape where AI systems are becoming ubiquitous. We observe two parallel developments that are transforming the industry and carrying significant implications for advertising practices. The first relates to ad targeting – the matching of ads with potential customers. Amidst the growing awareness of data privacy, tech giants limiting third-party cookies, and the enforcement of stricter regulations concerning the use of personal data in recent years, there has been an increased scrutiny of personalized targeting, i.e., methods relying on the personal data of consumers to distribute ads (Brodherson et al., 2023). This prompts the advertising industry to search for alternative targeting strategies. Contextual targeting, which relies on information about the content surrounding the ad space instead of personal data of consumers, has emerged as a leading alternative (Aridor et al., 2020; Bleier, 2021; Brodherson et al., 2023). The assumption behind contextual targeting is that the content users are consuming is related to their interests. Advertising a brand or product alongside related content should then increase the likelihood of this brand or product being relevant to the user. In this sense, contextual advertising is also tailored to the individual, but without using personal data. In other words, while personal targeting aims to target the right consumers, contextual targeting aims to target consumers at the right time (Lu et al., 2016).

The second development relates to the increased integration of AI into the advertising workflow. The increased power and range of AI available to advertisers have led to evolving marketing practices, where both ad creation and placement can be handled programmatically by machines (Chen et al., 2019). The available technology ranges from niche tools that enhance productivity, to outsourcing parts of the work – including decisions related to marketing budgets and advertising creatives – to full-fledged and autonomous AI systems (Haleem et al., 2022). Where programmatic advertising previously relied on simpler, rule-based automation, increasingly capable but opaque AI systems are becoming available to marketers.

This development promises increased scale and efficiency but also entails risks. For instance, recent research suggests that while disclosing that an ad has been placed by AI could potentially increase its effectiveness (Wu et al., 2024), consumer awareness of AI-generated content could have negative effects on the credibility of the ad and consumer attitudes toward it (Baek et al., 2024). Ads may also be placed automatically adjacent contexts that the advertiser wish not to be connected with. Both of the observed developments – concerning data used for targeting and the extent of using AI – involve crucial trade-offs for advertisers when devising advertising strategies. Based on these, we identify three key areas that necessitate careful consideration: results, resources, and rectitude. *Results* are the marketing objectives set for the ad campaign. *Resources* encompass hardware and software demands, financial resources, key skills, and data requirements for training AI models. *Rectitude* involves ethical considerations, privacy aspects, and regulatory constraints on the possessing, processing, and usage of data. When deciding on advertising strategies, these factors need to be considered when choosing targeting method and whether to involve AI or not in the automation process.

In this article, we identify different programmatic advertising strategies to choose between, discussing their pros and cons as to factors mentioned above. We provide practical insights into advertising strategy, with the goal of informing and guiding both marketing managers and academics. By incorporating perspectives from digital advertising, computer science, and media studies, this paper contributes to a deeper understanding of the evolving programmatic advertising ecosystem. A major contribution of this paper is our categorization of programmatic advertising, which has relevance for anyone working with programmatic advertising in practice.

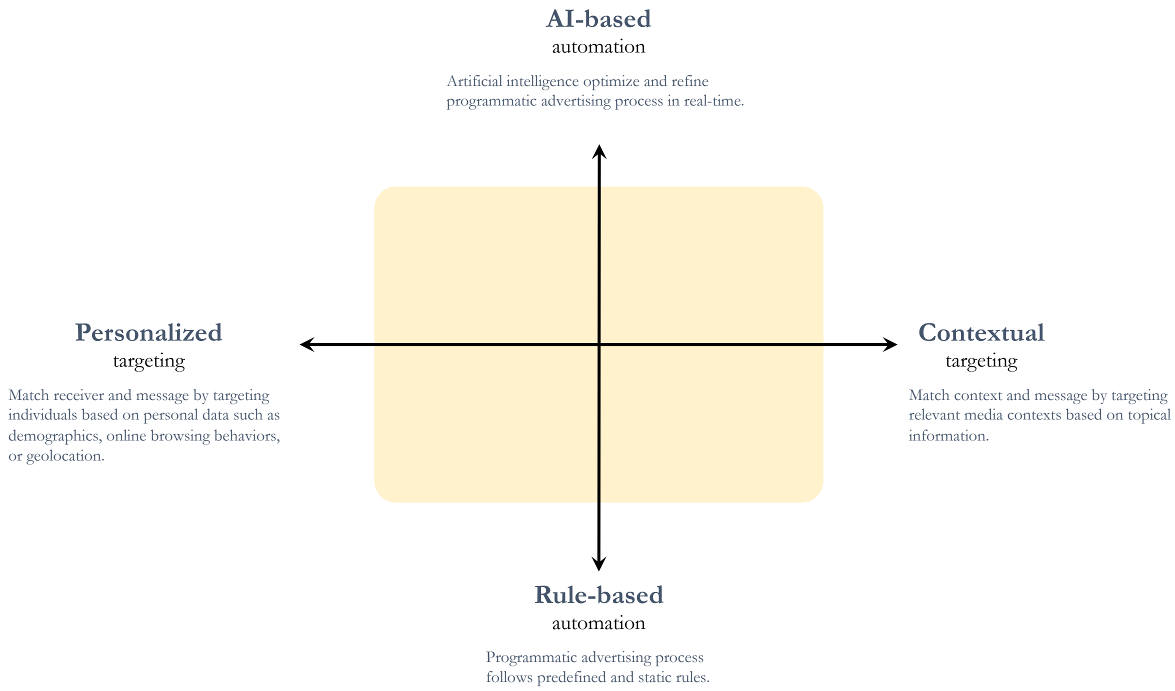
In the following section we consider the key decisions marketers face in when working with programmatic advertising. Next, we review factors influencing advertising strategy, organized under the key areas of results, resources, and rectitude. Finally, we discuss how adopting specific advertising strategies will be guided by practical implications.

2. Background

We identify two key aspects of programmatic advertising that makes the basis for programmatic advertising strategies: the data used for ad targeting, and the type of automation used in the distribution of ads. Ad targeting includes *personalized* targeting and *contextual* targeting. Understanding the essence of these two approaches is important since the industry need to balance the dependence on personal data and stricter regulations on the use of personal data, and a growing public awareness of and concern about data privacy issues.

Automation represents an ongoing industry shift from simpler *rule-based* automation tools to more complex *AI-based* automation systems. This distinction is important as it not only impacts the scalability and effectiveness of programmatic advertising, but also impacts the resources needed to run successful ad campaigns and introduces potential risks for advertisers.

Figure 1. Conceptual overview of programmatic advertising



2.1 Personalized targeting

Personalized targeting matches consumers and ads based on data about specific individuals (Tucker, 2014). It assumes that personal characteristics can be leveraged to improve messaging, as it allows an ad to be tailored and personalized to each user's inferred preferences. This can be accomplished through two approaches: adjusting the message itself (content personalization) or selectively exposing the message to specific individuals or groups of individuals (target messaging) (Boerman et al., 2021).

The practice of dividing audiences into smaller market segments – based on factors like demographic characteristics (e.g., gender or age), behavior (e.g., non-users, light users, or heavy users), brand awareness (e.g., unknown or well-known), or attitudes (e.g., favoring one's brand or a competitor's brand) – predates the internet (Wedel & Kamakura, 2000; Yankelovich & Meer, 2006). However, in online contexts, personalized targeting can also exploit other capabilities than are available offline, for example behavioral data such as browsing history, shopping habits, social media interactions, and other types of personal behavioral data, and in much higher volume, velocity, and variety. To automate and streamline these large-scale data processes, marketers are increasingly using AI (Haleem et al., 2022).

The practice of logging consumers' web-browsing behavior and then using these data to place ads is known as online behavioral advertising, or OBA (Boerman et al., 2017; Varnali, 2021). This was developed to increase the click-through rates for ads (Zuiderveen Borgesius, 2015). OBA constitutes a vast part of online ad targeting today (Neumann et al., 2019). Within OBA, the granularity of the data available to advertisers and the level of specificity in which the ad is tailored to the individual, can vary greatly. On the highly tailored end of the personalization spectrum is retargeting, where users are shown ads for brands or items that they have previously engaged with, in an attempt to get them to come back. While proven to be effective, retargeting can be perceived as privacy-invasive by consumers (Aiolfi et al., 2022; Bleier & Eisenbeiss, 2015b).

On the less tailored end of OBA is interest-based targeting, where an ad is targeted towards groups of consumers sharing similar interests rather than to individual consumers. In addition to data such as IP addresses and geolocation, which enable the delivery of localized or region-specific advertisements based on users' geographic locations, OBA leverages data trails which are more commonly left unknowingly or passively by the user. These include web searches or viewed content, but also self-reported data, for example, registration data (Ahrens & Coyle, 2011). Various online platforms, including social media sites, e-commerce platforms, and newsletter subscriptions, often mandate users to provide demographic details during registration.

Thus, it is important to consider how the data used for targeting has been sourced, as well as to distinguish between first-party and third-party data. First-party data are collected by advertisers through their (or their customers') own channels, for example, registration of demographics to a user account or a user's search and purchase history on the company's website. Third-party data are collected by cookies or other tracking technologies (e.g., fingerprinting, web beacons, or pixel tags) by another entity.

Compared to traditional advertising methods, personalized advertising has been shown to deliver significantly higher engagement, relevance, and return on investment (Arora et al., 2021; Boudet et al., 2019). A key reason for why personalization is effective is by making the ad feel more relevant (De Keyzer et al., 2022), but this has to be balanced against the risk of (real or perceived) violation of customer privacy rights. The relation between risks and benefits of personalized advertising has given rise to the so-called "personalization paradox" (Aguirre et al., 2015). This means that personalized advertising can result in both an effective and ineffective advertising strategy: it can increase the relevance of the advertisement, which stimulates attractive outcomes such as click-through rates, but can at the same time give rise to a negative feeling of exposure, which increase the likelihood of avoiding the advertisement (Turow et al., 2009), lowering the number of clicks (Boerman et al., 2021).

2.2 Contextual targeting

The main assumption behind contextual targeting is that the content a user is currently consuming is indicative of their interests or state of mind and can hence be leveraged for advertising purposes (Häglund & Björklund, 2024). The ad and context can, for example, be from the same category (advertiser thinks that congruency between context and ad is good), or from distinct categories (advertiser view the context as a proxy for other interests, which can be correlated with the focus of the ad), or be such that the content primes for associations that are beneficial for the ad.

Previous research indicates that users tend to engage more with advertisements that are placed on websites featuring similar content as the ads (Wojdynski & Bang, 2016). In such instances, users may perceive the ads and webpages as a joint unit, leading them to coherently read and interpret the content (Åbonde Garke et al., 2021). This can make the presence of the advertisement less intrusive, as it aligns with the users' overall experience and interests. A related phenomenon is (delayed) contextual priming (Minton et al., 2017). It suggests that when users browse websites, they are initially stimulated by the content. Later, when they come across an advertisement that relates to the content they have been viewing, it serves as a reinforcing second stimulus which deepens their memory of the advertised product (Minton et al., 2017; Yi, 1991).

Traditionally, online contextual advertising has been performed by core element analysis of web-page content (Silvennoinen & Jokinen, 2016). Advertisers and advertising agencies can, for example, analyze the contextual content of web pages to extract keywords or topics. These keywords or topics can be utilized as rules to filter opportunities for displaying ads. The level of generalization in formulating such rules aligns with the complexity involved in employing AI-based automated advertising policies. For example, advertisers have the option to allow the system to bid on any sports websites or utilize precise rules, which comprises elaborate metrics including numerous keywords and specific topics, to precisely target the websites on which they wish to display their ads (e.g., only websites about certain sports, professional leagues, or teams). AI-based tools are also capable of identifying and analyzing more complex multimodal features of website contexts, such as images and videos, and overall provide more detailed and nuanced analysis of contexts enabling more precise contextual targeting (Häglund & Björklund, 2024).

Although we discuss contextual advertising as matching ads to web page content, there is no consistent industry or academic definition of the term. Contextual advertising has sometimes simply been defined as “non-behavioral” or “non-personalized,” emphasizing its privacy-preserving nature compared to targeting using consumer data (Bleier, 2021; Google, 2024). However, the line between contextual and personalized advertising is not always as distinct as one might think. According to some researchers and industry actors, data such as the users’ behavior within a browsing session, geo-location data, or connections between users, are all contextual (Bleier, 2021; Lian et al., 2019). Another ambiguous case between what should be characterized as contextual or personalized advertising is the matching of ads to user-generated content, such as social-media posts or product reviews.

2.3 Rule-based automation

The second aspect refers to the type of automation that programmatic advertising relies on for distributing ads. The first type relates to simpler rule-based automation, where humans perform most actions and make decisions as to where to place ads. In these cases, marketers are aided by tools and systems of various sophistication and the placements of ads are deterministic. Common to all rule-based automation are their dependence on human input, rule-setting, and oversight (Hicham et al., 2023). This type of automation can be compared to a pocket calculator. The calculator can perform a range of operations, some quite advanced, but the user still needs to push the buttons and interpret the result on the display for anything to happen. Although not as powerful as AI-based automation, they dutifully adhere to human-designed rules, alleviating repetitive and mundane tasks.

In the case of rule-based systems for programmatic advertising, advertisers can predefine the ad delivery targets through demand-side platforms (DSPs), specifying bidding factors such as targeted website, demographic segments, bidding duration, and targeted geographical location (Schäfer & Weiss, 2016). Under these rules, the bidding system still has some degrees of freedom to optimize the bidding process, but the general strategy is set. The advertiser can then observe the campaign performance metrics and adjust campaign settings to try and optimize the results going forward.

2.4 AI-based automation

The second type of automation is AI-based automation. The rapid advancement of AI technology has changed the pre-requisites and potential of programmatic advertising. The global scale of campaigns, the demand for real-time decision-making, and the quest for more insightful user analysis involved in programmatic advertising have motivated advertisers to increase the use of autonomous technologies. Compared to rule-based automation, AI-based automation have a higher degree of autonomy with respect to bidding, distribution, and optimization of online ads. This class of systems relies on AI models, which are often large and opaque (Hicham et al., 2023). In such implementations, AI exhibits a higher degree of flexibility, enabling it to make "autonomous judgments" that surpasses the specific instructions provided by humans.

AI-based programmatic advertising expands the level of independence within the system or AI techniques, to make decisions during the whole bidding process. For instance, training a reinforcement learning real-time bidding agent enables it to continuously learn and develop the best bidding strategy through accumulated bidding attempts (Cai et al., 2017). This empowers the agent to learn the optimal bidding strategy within the limited bidding opportunities and budget. Another use is to improve the advertisers' understanding of available data and help them perform complicated operations at scale, including techniques to classifying consumer or content data into segments to generate actionable insights (J.-A. Choi & Lim, 2020).

Deep learning (Hinton et al., 2006), a technique for improving AI-based automation using neural networks, have performed well in domains such as computer vision and natural language processing, although often at the expense of explainability – the ability to understand the rationale of the AI systems' decisions. The capabilities of deep learning have driven success in programmatic advertising by enabling audience segmentation, media content classification and precise prediction of advertising metrics such as clicks and purchases through analysis of big data (J.-A. Choi & Lim, 2020; Häglund & Björklund, 2024). The latest frontier in deep learning, Generative AI, leverages powerful models like LLMs, image, and video models. Trained on massive datasets, these models achieve astounding performance across a spectrum of tasks often without the need for extensive adaptation for specific applications. In programmatic advertising, large generative models could reduce the need for extensive training dataset or historical campaign data to distinguish audience or content segments (Häglund & Björklund, 2024). Moreover, generative capabilities enable increased granularity in ad messaging through tailored ad creative and messages (Amankwah-Amoah et al., 2024). When integrated with reinforcement learning, deep learning not only enhances the advantages of learning in dynamic environments but also enables the algorithm to conduct in-depth data analysis and effectively tackle complex and multidimensional challenges (Wang et al., 2020). In intelligent programmatic advertising, the algorithm gains the ability to adapt and improve its bidding decisions based on real-time feedback and optimization techniques (Cai et al., 2017; Zhao et al., 2021). While AI techniques like deep learning and generative AI can be tuned and updated automatically, reducing the need for manual operations, it remains crucial for humans to define the logic and goals of these algorithms and supervise their actions.

2.5 Summary of key choices in programmatic advertising practice

The above sections describe the two aspects of programmatic advertising which advertisers need to make decisions about – targeting method and type of automation used. Common for all strategies is that humans will define campaign success criteria, and algorithms will handle the bidding for ad space (through real-time bidding). While the type of automation an advertiser relies on is discrete (it either involves AI or not), the data used for targeting are more nuanced (an advertiser can rely on either type of data, or a combination of both).

By combining type of targeting (contextual/hybrid/personal) and automation (rule-based/AI-based) we arrive at six potential ad strategies to choose from in practice. These are presented in Table 1.

Table 1. Programmatic advertising strategies.

Potential ad strategies will consist of a combination of targeting and automation. The choice of targeting involves contextual or personal data, or a mix of the two. The choice of automation relies either on simpler rule-based or more complex AI-based

	Contextual targeting People are targeted at the " right time" by matching message and context (ads are matched with the content of a website, app, video etc.).	**Hybrid targeting** The " right people" are targeted at the " right time" by matching message with context and receiver (ads are matched based on contextual content and personal data).	**Personalized targeting** The " right people" are targeted by matching message and receiver (ads are matched with individuals based on personal data like demographics, online behavior, or geolocation).
AI-based automation Ad distribution systems improve campaign performance through ongoing optimization. Marketers set campaign goals and can provide starting points for AI to experiment with (e.g., try or avoid certain contexts or audiences). Ad creative can be adapted based on feedback.	**1.** **AI decides where ads should be shown.** Ads are placed based on advanced contextual analysis (e.g., topic modelling, sentiment analysis) and dynamic optimization (real-time adjustments to target contexts and ad creative based on campaign performance).	**2.** **AI decides where ads should be shown and to whom.** Ads are placed using both contextual and personal signals (advanced contextual analysis combined with predicted user engagement) and optimized dynamically based on feedback.	**3.** **AI decides to whom ads should be shown.** Ads are placed based on predicted engagement of specific individuals (e.g., based on behavior and stated or inferred preferences and other characteristics) and dynamic optimization (ads are tailored in real-time on the user-level).
Rule-based automation Ad distribution systems followspredefined and static rules. Marketers set campaign goals and other criteria like bid price and targeting settings. Ad creative is fixed.	**4.** **Marketer decides where ads should be shown.** Ads are placed in predefined contexts. Ranges from specific websites (e.g.,), to matching by keywords (e.g., " solar panels") or topics (e.g., " sports blogs").	**5.** **Marketer decides where ads should be shown and to whom.** Ads are placed based on predefined user segments and predefined contexts. Combining basic segmentation (e.g., certain demographics) with content matching (e.g., particular topics).	**6.** **Marketer decides to whom ads should be shown.** Ads are placed based on predetermined user segments, like demographic information (age, gender, location) or broad interest groups (e.g., " people interested in outdoor cooking").

While there are six potential programmatic ad strategies a marketer could pursue, as illustrated in Table 1, we argue that only four are relevant in practice; the hybrid targeting approaches are subordinate to personal targeting. The reason for this is that there are two big trade-offs in practice: (1) whether to use AI or simpler rule-based automation, and (2) whether to use personal data or only contextual data when targeting consumers, which both offer routes to effective advertising, but at the same time involve certain risks for the advertiser. We will now give examples of these four programmatic ad strategies, before discussing the risks at length in the next section.

The first strategy represents an advertiser that relies on rule-based automation to perform personalized targeting. The advertiser will bid for impressions based on personal data or a combination of personal and contextual data – such as interests inferred from a consumer's browsing patterns or demographic information. While algorithms will perform the matching of ads and impressions, it will be up to the advertiser to rely on their domain expertise to define which segments or audience profiles to target. Consider, for example, that the advertiser wants to market gardening tools. Towards this end, the advertiser might decide, based on previous experience and market research, that the best approach will be to target middle-aged people living in houses in suburbs.

The second strategy represents an advertiser that relies on an AI-based automation to perform personalized targeting. The advertiser will also in this case bid for impressions based on personal data or a combination of personal and contextual data, but decisions about profiling and targeting will be made by an AI system – which has been trained on historical ad-campaign performances. For our gardening tools, AI might target people of all ages that show a browsing pattern indicating they are interested in gardening or have recently moved from an apartment to a house.

The third strategy represents an advertiser that relies on rule-based automation for contextual targeting. The advertiser bids on ad impressions that are identified based on certain topics or keywords found on websites or in apps, but uses their own domain expertise to decide what content is relevant to match with their ads. Importantly, no personal data about consumers are used in this scenario. For example, the advertiser with the gardening tools may decide to bid for ad impressions on websites which relate to do it yourself projects and home improvement.

The fourth strategy represents an advertiser that relies on an AI-based automation for contextual targeting. Here, the advertiser will bid for impressions based on keywords or topics, corresponding to contexts which AI decide are attractive to pursue. Again, no personal data is relied upon. For the gardening tool campaign, the AI might find that the optimal contexts are outdoor sports forums – these are undervalued contexts where bids are cheap and the audience (which use certain garden tools while bush crafting) typically have high willingness to pay for quality gear.

It seems likely that the future of programmatic advertising will, to an increasing extent, rely on AI-based automation and a hybrid targeting approach. The main reasons are that many advertising platforms will tend to push their users towards using the maximal amount of data available (i.e., a combination of both personal and contextual information) and that, in an increasingly competitive ad landscape, many ad platforms will develop more complex tools (i.e., AI-based automation) which they will urge their users to employ.

It is easy to see the appeal of such a development: by using more data for targeting and AI-based automation, ad strategies can be perceived as having an edge in terms of effectiveness compared to strategies relying on less data and "simple" rule-based automation. For this reason, we believe that uninterested or unknowing advertisers will most likely end up with an AI-based and hybrid data ad strategy. But there are important drawbacks for advertisers to consider, such as cost and, as we will see, the possibility to understand the rationale for the decisions these systems make.

3. Factors influencing choice of programmatic ad strategies

There are several factors that will influence what ad strategies are possible, as well as attractive, for advertisers to pursue. We propose that these influencing factors are categorized into three areas: results, resources, and rectitude. *Results* cover the marketing objectives which a campaign is aimed at fulfilling, such as long-term brand building or short-term sales. *Resources* concern issues such as evolving technologies, data used, expertise, capacity, and financial means. *Rectitude* is related to ethics, privacy, legal regulations, and data handling restrictions. An overview of the influencing factors and their mapping to the different ad strategies is offered in Table 2.

Table 2. Factors influencing the choice of programmatic ad strategy

	STRATEGY			
	AI contextual	**AI personal/hybrid**	**Rule-based contextual**	**Rule-based personal/hybrid**
Results				
Finding undervalued impressions	Very high	Medium	Very low	Very low
Reach new audiences	Very high	High	High	Low
Brand building	Very high	High	Medium	Medium
Conversions	Medium	Very high	Low	High
Customer retention/loyalty	Low	Very high	Very low	High
Reactivating dormant customers	Very low	Very high	Very low	High
Resources				
Budget requirements	High	Very high	Low	Medium
Time to setup campaign	Medium	High	Low	Medium
Data requirements	Medium	Very high	Very low	Medium
Optimization/ maintenance needs	High	Very high	Low	Medium
Technical expertise needs	High	Very high	Low	Medium
Legal expertise needs	Medium	High	Very low	Medium
Computational resources/energy use	High	Very high	Low	Medium
Rectitude				
User privacy risk	Low	Very high	Very low	High
Algorithmic bias risk	Low	High	Very low	Medium
System opacity (how the algorithm works)	Medium	High	Low	Medium
Reputational risk (brand safety)	Low	High	Very low	Medium
Regulatory compliance burden (e.g., GDPR)	Low	Very high	Very low	High
Risk of third-party data limitations	Low	High	Low	Medium
Platform dependencies (risk of rule changes)	Medium	High	Low	Medium

3.1 Results

Results are the outcomes of a campaign, reflecting its intended objectives or marketing goals.

There are many different possible results an ad campaign might work to achieve. A common division is between short-term sales goals and long-term brand goals (H. Choi et al., 2020; Yun et al., 2020; Zhu & Wilbur, 2011). Personalized targeting, drawing on historical behavioral data and customer characteristics, excels at short-term performance metrics like reaching users with high purchase intent or existing brand familiarity. The ability to leverage detailed customer insights enables marketers to deliver highly relevant messages that can trigger immediate responses (Bleier & Eisenbeiss, 2015a). Even relatively simple personalization techniques can yield significant results – for instance, adding the recipient's name to email subject lines can increase open rates by up to 20% (Sahni et al., 2018). A common use for personalized targeting is retargeting efforts, where effectiveness increases in proportion to the depth of available customer data product preference information (Lambrecht & Tucker, 2013). The timing of retargeting is crucial, however, with campaigns showing highest effectiveness close in time to initial website visits (Sahni et al., 2019).

Contextual targeting tends to align well with long-term goals such as broader brand-building objectives or reaching new audiences. By placing ads in favorable media contexts, contextual targeting can foster positive brand associations and build brand equity (Häglund & Björklund, 2024). This approach can be particularly effective in initial consumer interactions, where the goal is to introduce the brand to prospective customers who may not yet be actively searching for the particular brand or its products. By targeting consumers are the right time, i.e., in appropriate contexts, contextual advertising allows marketers to find and attract new audiences (Lu et al., 2016).

While both personalized and contextual targeting have their strengths, several studies point to the potential of combining these approaches. This hybrid approach can be highly effective and achieve both short-term performance goals and long-term brand objectives (Bleier & Eisenbeiss, 2015a; Ghose et al., 2019; Lu et al., 2016).

Employing AI might not change the overall advertising process, but it makes it more efficient throughout (Qin & Jiang, 2019). The purpose of advertising algorithms is to optimize bidding strategies and maximize advertising effectiveness. Early machine learning algorithms exploited historical data for revenue predictions (Perlich et al., 2012; Zhang et al., 2014). While these approaches offered advertisers guiding statistical suggestions, they proved insufficient in the dynamic and rapidly evolving online landscape of programmatic advertising. Recently, more advanced AI-driven algorithms – which incorporate deep learning techniques – have emerged, promising higher accuracy and adaptability to dynamic advertising environments. Some of these novel solutions integrate reinforcement learning to optimize bidding strategies even within constrained budgets (He et al., 2021), while others incorporate attention mechanisms to enhance interpretability (Jose & Shetty, 2022). Additionally, improved user segmentation and targeting technologies enhance programmatic advertising optimization through a blend of static demographic tags, continuous user behaviors and implicit contextual-driven segments (J.-A. Choi & Lim, 2020).

As such, AI-based automation promises to augment both personalized and contextual targeting, for example leading to improved performance by identifying valuable opportunities that might be missed by rule-based systems. For example, personalized targeting could become more effective through more sophisticated consumer analysis. As a recent study showed, using AI to predict consumer personality traits enabled improved ad matching and, consequently, ad effectiveness (Shumanov et al., 2022). Another possibility, we believe, for AI in personalized targeting can be to revive old customer relationships. Through more advanced data analysis, it should be possible to tailor messages with the purpose of reactivating dormant customers.

AI could also improve contextual targeting through its superior ability to analyze nuanced content relationships and semantic structure. This enables more sophisticated placement decisions, as the system becomes better at categorizing and identifying promising contexts. This way, AI might make contextual targeting more brand safe, by better avoiding bad contexts, and effective, by better finding favorable contexts (Häglund & Björklund, 2024).

The promise of AI-based automation, we believe, is that both targeting approaches might become more flexible, allowing them to work towards more diverse goals. We see how AI could be used to find undervalued impressions to bid for, by identifying consumer segments or contexts that are typically either missed or ignored. Consequently, the distinction between contextual and personalized targeting could become less clear-cut with AI-based automation, as both targeting approaches demonstrate broader capability ranges than their rule-based counterparts.

3.2 Resources

Resources are concerned with what capabilities and means are available to the marketer. This includes technologies, access to data, technical and legal expertise, and financial means.

The rapid advancement of complex advertising algorithms and systems relies heavily on access to large amounts of robust data. This is particularly crucial for AI-driven implementations, and especially when combined with personalized targeting. Indeed, for personalized targeting, more personal data typically leads to better results (Malthouse et al., 2018). With less data, the advertiser is pushed towards rule-based automation and contextual targeting. This is not necessarily negative, but it is more limiting in terms of the scalability and precision of targeting that, in particular, AI can offer.

By utilizing extensive datasets from external sources, advertisers can refine customer profiles, segment markets, and deliver personalized services at scale, improving the advertising experience. However, challenges arise as data are often aggregated from various sources. Third-party data can be outdated and inaccurate, making the reliability and quality questionable, and this is hard to control as the data collection process is often hidden. Consequently, data accuracy and segment validity remain uncertain, which potentially can be costly for advertisers. As Mark Thompson, CEO of the *New York Times*, asked in a discussion with *AdExchanger* on Ad Tech reform; "When we say someone is a member of the audience is a female fashionista aged 20-30, what's the probability that that's actually true?" (Rodgers, 2017).

Given the substantial changes in online data privacy, advertisers have come to place a higher value on first-party data. However, obtaining such data requires initiating multiple transactions on different self-service platforms. Advertisers can proactively engage with users and collect data through chats, social media, surveys, or homepage logins. To avoid negative side effects, it is crucial to review the user experience during the data collection process and analyze data thoroughly afterward. Since first-party data originate directly from the users and are owned by the data collector, these data holds a higher degree of relevance and transparency to the ads or products compared to third-party data. This is essential, since data accuracy forms the basis of informed decision making. Additionally, the concept "zero-party data" has gained advertisers attention, differing from the first-party data in users willingly sharing their information for personalized experiences (Figas, 2023).

While programmatic advertising is undoubtedly a powerful tool that opens many possibilities for advertisers and publishers, the success of their initiatives heavily relies on the platforms and agencies responsible for managing programmatic ad campaigns, with tech giants like Google leading the charge due to their extensive data collection, advanced algorithms, and efficient ad management platform.

For advertisers, an alternative method to diminish reliance on “external unknown” architectures and operations, is to bring the entire programmatic trading process in-house by exploiting first-party data. This grants advertisers full control over the technology, data, transparent internal communications, and desirable operations aligned with their objectives. As an illustrative example of a successful case, the pharmaceutical giant Bayer began their in-house programmatic advertising in 2017, reduced their programmatic ad buying costs by over $10 million within the first six weeks and acquired a diverse range of resources, including their own tech stack and data (Basis Technologies, 2023).

However, the deployment process can take up to a year before the system becomes operational (Broussard & IAB, 2018). Implementing in-house systems of this scale is not feasible for every company. During this period, advertisers must recruit skilled professionals well-versed in every facet of the process, including but not limited to strategy optimization, data analysis, algorithm development, and system maintenance. Bringing the system to official operation demands financial means, collaborative efforts from every department within the company, as well as rigorous testing.

For these reasons, some advertisers choose to outsource technical tasks while retaining control over essential components (M. Sweeney, 2020). Outsourcing significantly accelerates the technical implementations through bypassing employee recruitment and training efforts. However, advertisers must exercise cautiously and evaluate the quality and accountability of outsourced technology partners considering their budgets.

Access to technological competence will give the advertiser greater flexibility in selecting ad strategies. With internal technologies, they can fully utilize the latest tools and systems to make informed strategic decisions. Without such expertise, advertiser is pressed to rely on the default, often AI-driven, implementations offered by the ad platforms. Whenever personal data is involved, advertisers must also ensure adequate legal expertise to navigate privacy regulations and data protection requirements, as mishandling can lead to significant legal consequences. AI-based automation adds another layer of complexity to the ad process, which further warrants the need for legal expertise, particularly when paired with personalized targeting (see *3.3 Rectitude* below).

3.3 Rectitude

Rectitude encompasses various risks and challenges that advertisers must carefully consider and manage. These range from technical and operational risks to ethical and regulatory concerns.

A primary concern is algorithmic bias. Personalized user attributes are often inferred from behavioral data, such as assumed user interests, perceived demographics, or “look-alike” audiences. Algorithmic profiling introduces bias, as machine learning algorithms are inherently imperfect, and some misclassifications are more impactful than in others. Profiling algorithms also tend to erase smaller and marginalized groups; for instance, encoding gender binary misclassifies non-binary individuals, even if they disclose this information. For automated ad placement, algorithms match ads to target users, typically optimizing metrics like click-through rates. Greater automation improves ad delivery but can introduce bias and generalizations. For example, gender-neutral STEM (science, technology, engineering and mathematics) career ads on Facebook were shown to far fewer women than men (Lambrecht & Tucker, 2019).

The EU Digital Services Act (DSA), adopted in 2022, bans targeted ads based on sensitive data like ads profiling children, ethnicity, political views, or sexual orientation (European Commission, 2023). Globally, targeted advertising is generally illegal if it discriminates against protected classes such as gender, race, religion, national origin, marital status, or age, with housing, credit, and employment ads particularly vulnerable to such bias (Corrêa, 2022). Facebook has settled lawsuits for allowing employment, housing, and credit ads targeting based on gender, ethnicity, and age (Corrêa, 2022). Additionally, the company faces US lawsuits for biased algorithmic decisions, including not showing insurance ads to women and older people, violating civil rights laws (Roth, 2023). While major ad platforms must comply with anti-discrimination legislation, their systems can still allow unintended discriminatory outcomes. Advertisers should monitor and avoid certain targeting settings to mitigate these risks. Using less personal data through contextual targeting and opting for rule-based ad choices can reduce, but not eliminate, the risk of discrimination.

Interpretable user-ad matching relying on simple user categories, assumes authentic user profiles are available, which are rare due to privacy legislation. Without complex optimization algorithms, the advertisers choosing the target categories is directly responsible for ethical ad distribution, making intentional and unintentional discrimination easier to trace and follow up on. However, simpler design does not mean that discrimination is less common as it arises through correlations between categories or “look-alike” targeting (Speicher et al., 2018). This can narrow the audience as advertisers may target based on stereotypes rather than actual target, such as advertising hair products to women instead of, “people with long hair”.

With growing access to user data, advertisers must increasingly prioritize ethical norms and societal impacts of advertising. While some advertising limitations like restrictions on advertising towards children and fundamental rights to privacy, are legal, most ethical decisions rest with advertisers or publishers. Relying on algorithms for ad placement reduces control but not responsibility, requiring an understanding of the technology to guide ethical choices.

Personalized advertising relies on profiling, using data users provide explicitly or implicitly. Profiling may involve human-readable matches or complex algorithmic models, but ethical concerns persist regardless of the approach. Personalized advertising risks include discrimination (e.g., targeting job ads by age or gender), exploiting vulnerable groups (e.g. betting ads to gambling addicts), breaching privacy (e.g. revealing sensitive health data via recommended ads), or stereotyping (both reinforcing stereotypes and erasing smaller groups) (Ali et al., 2019). These risks exist in both rule-based and AI-based automation, through rule-based methods allow more ethical control. While contextual targeting has flaws, it carries fewer ethical risks.

System opacity presents another significant challenge. Creating and training algorithms add another layer of opaqueness. Larger machine learning models, those for image and text analysis, are often based on “pre-trained” or “foundational” models. While the models may be documented or even available under an open-access policy, the data used for training are rarely documented in full. For instance, using large language model for matching articles with ads, makes it impossible to verify that no personal data were used in the decision. Additionally, there is no direct control over the amount of historical data a pre-trained model uses, and in the advertising industry, the timeliness of training data can be critical.

Contemporary AI algorithms, often referred to as “black boxes” tend to be highly opaque even for their own developers. If an unethical or illegal ad is shown, it is often impossible to determine whether it is a bug, an (unlikely) expected outcome, or intentional abuse, leading to reputational risk for the advertiser rather than the vendor, even if the vendor is open about their algorithmic solutions. A major type of personalized advertising abuse that drives the increased control over online advertising, is the misuse of political profiling which can undermine democratic institutions. The attempts to influence elections through targeted messaging and spreading of fake news, has raised concerns about its impact on democracy, with Cambridge Analytica being a well-known example (Berghel, 2018; Wylie, 2019). Though restrictions on personalized advertising make targeting swaying voters harder, advanced context matching could still enable disinformation or intimidation campaigns.

A fully automated system, where algorithms optimize ad campaigns based on the results of placements done by another algorithms, could be highly efficient. However, this makes decisions harder to trace, and any issue may fall on the advertiser. Simpler less automated approaches reduce risks (e.g., a vendor using smaller machine learning models with in-house data), but risk remain with any data-based algorithm For an advertiser, AI-based automation may carry higher risks than rule-based automation.

Privacy risks are particularly significant. Behavior-based ads may reveal information about previous search history, or in extreme cases, suggest belonging to a marginalized group or a specific health condition, potentially endangering the individual. Growing public awareness of data privacy and stricter legislation push firms to rely less on personal data. Personalization is double-edged: while users expect and want it, and it boosts revenue growth (Arora et al., 2021; Morgan, 2020), it risk infringing on privacy and perpetuating harmful biases (Boerman et al., 2021). Data privacy legislation may not severely impact all advertisers, but compliance can be challenging, especially for international businesses navigating diverse legal standards. Adapting to new regulations and platform changes adds uncertainty and costs. A "one-size fits all"-approach can simplify compliance but may result in missed opportunities seized by more adaptable competitors.

Regulatory compliance presents increasing challenges overall. Data privacy regulations are driving a shift away from personalized advertising (Aridor et al., 2020; Brodherson et al., 2023), forcing advertisers and publishers to abandon or adjust targeting practices. Notable privacy legislation include the GDPR (EU), the UK Data Protection Act, and the California Consumer Privacy Act (Greenleaf, 2021). While such legislations require changes, their economic impact has been less severe than feared. GDPR has reduced trackable consumers by 12.5 percent in affected countries (Aridor et al., 2020), but most still consent to tracking and opt-in extract tracking periods, offsetting the effects of consumer fallout.

Platform dependencies and third-party data limitations pose additional risks. Changes by Apple Safari, Mozilla Firefox, and Google Chrome to reform or end third-party cookies support, will significantly impact user analytics, targeting, and conversion attribution (Zawadziński & Sweeney, 2019). Strategies like using first-party data, or adopting contextual targeting, or alternatives like Google's "Privacy Sandbox", can reduce reliance on third-party data and mitigate regulatory risks. This initiative seeks to improve online services while protecting user privacy. The Privacy Sandbox introduces "Topics API", which tracks browsing to identity topics without compromising user data (Dutton & White, 2021). Alternatives to third-party cookies include "Data Clean Rooms", which encrypt data, and "Seller Defined Audiences", which use first-party data transparently (M. Sweeney, 2023). Contextual targeting also offers a privacy friendly option by avoiding personal data entirely.

Resilient advertisers provide valuable experiences where users willingly share data. Industry research shows marketers increasingly allocate budgets to big tech ecosystems for access to large audience and consumer insights. Meanwhile, data partnerships are growing in sectors like consumer goods, pharmaceuticals, travel, and grocery, facing challenges in unifying customer identification while protecting consumer privacy (Brodherson et al., 2023).

With the rise of generative AI tools, technology can influence beliefs, emotions, and behavior (Makridakis, 2017). In advertising, this can for example include manipulative use of contextual advertising. Examples can involve strategically placing payday loan ads within financial hardships fora and using so called "dark patterns," such as disguised ads, ambiguous language, or misleading consumers into unintended actions (Fair, 2022). The American Federal Trade Commission (FTC) raises these issues specifically in relation to generative AI and advertising and warns that tricking consumers into making harmful choices are a common element in FTC cases under consumer protection law (Atleson, 2023). According to the Advertising Standards Authority (ASA), a self-regulatory body within the UK's advertising industry, it remains the primary responsibility of advertisers to ensure the compliance of their advertisements and targeting practices, even when marketing campaigns are entirely generated or distributed through automated means (ASA, 2023).

The rise of AI in advertising brings additional regulatory scrutiny. The EU Artificial Intelligence Act (EU AI Act), adopted in 2024 is the first comprehensive law designed to ensure the safe and ethical use of AI. While predicting precisely how it will be applied to advertising remains uncertain, certain aspects such as AI-generated ad content, manipulative advertising, and political messaging are likely to undergo scrutiny (Adam & Hocquard, 2023; European Parliament, 2023). Advertisers need to be prepared to answer questions from regulators about how they are using AI for ad targeting, especially when there are risks for unfair outcomes or consumer manipulation. The FTC provides guidelines on how to promote fairness and prevent discriminatory outcomes when employing AI and algorithms (Jillson, 2021; Smith, 2020). Transparency about methods collecting sensitive data, and for what purposes AI is used, is the first point of emphasis. Explainability, the ability to provide rational for algorithmic decision-making, is another.

One alternative to mitigate some of these risks is switching to contextual advertising. By matching ads on context rather personal data, contextual advertising reduces risks like exposing sensitive data and discourages predatory practices (e.g., individuals with gambling addictions see online casino ads, no more frequently than other individuals on the same pages). However, while contextual advertising can reduce such risks, it can still reinforce societal biases through harmful context-ad matches (L. Sweeney, 2013).

3.4 Summary of key considerations

There are many things to consider when deciding on a programmatic ad strategy. We acknowledge that it can be hazardous to give recommendations in a rapidly changing field; the "optimal" outcome is necessarily a moving target. There are, however, two main choices which have clear implications for programmatic ad strategy, even though the particulars continue to change: what data to use when targeting consumers, and what type of automation to rely on. Our analysis of programmatic advertising strategies reveals clear patterns in how different approaches serve various marketing objectives (see Table 2). Contextual targeting demonstrates particular strengths in the upper parts of the marketing funnel, consisting of longer-term objectives, where it excels at building brand awareness and reaching new audiences. This makes intuitive sense, as contextual targeting focuses on matching ads with relevant content environments rather than specific user profiles, making it ideal for reaching potential customers who are discovering brands and products through their interests and current browsing behavior.

In contrast, personalized targeting shows its greatest value in the latter stages of the marketing funnel, consisting of short-term results, proving especially effective at driving purchases, fostering brand loyalty, or reactivating dormant customers. This targeting method leverages known user characteristics and behaviors, making it particularly powerful when past actions can help predict future purchase intent or when nurturing existing customer relationships.

The introduction of AI acts as a multiplier for both targeting approaches: it enhances their inherent strengths through more advanced pattern recognition and predictive capabilities, and extends their suitable use cases (making them work over a larger part of the marketing funnel). When applied to contextual targeting, AI enables more nuanced content matching and audience discovery. When used with personal data, it allows for more precise audience segmentation and behavioral prediction. However, this increased sophistication comes with notable tradeoffs. AI-based strategies require significantly more resources, including higher budgets, specialized expertise, and robust infrastructure. They also introduce greater complexity in terms of maintenance and optimization needs. Perhaps most importantly, AI-based approaches, especially when combined with personal data, raise substantial regulatory and ethical considerations that must be carefully managed.

4. Discussion

In this article, we have provided a conceptual overview of programmatic advertising and discussed factors which influence the choice of ad strategies. We introduced a framework for thinking about programmatic advertising strategies, which involves choices between personalized and contextual targeting, and rule-based and AI-based automation. Furthermore, we discussed the importance of assessing available resources, the significance of rectitude and ethical considerations, as well as compliance with legal regulations, when implementing programmatic advertising strategies.

There are trade-offs between personalized and contextual targeting strategies. Personalized advertising allows for highly tailored and individualized messaging, which can increase the relevance of the advertisement and potentially lead to higher click-through rates. However, it may also give rise to negative feelings of exposure and invasion of privacy among users. Contextual targeting, on the other hand, relies on the assumption that consumers who spend time in a certain digital context would be more receptive to certain ads. While this approach preserves user privacy and avoids reliance on personal data, it may not be as precise in reaching specific individuals. The complementary nature of these targeting methods suggests that marketers might benefit from deploying them strategically at different stages of the customer journey, rather than viewing them as competing alternatives.

There is also evidence suggesting that the hybrid approach, using both personal and contextual data, when targeting ads can be very effective (Ghose et al., 2019; Lu et al., 2016). This would allow the advertiser to serve information and offers that are relevant to the receiver and provided at the right moment. A vegan arriving in a new city might be guided to restaurants with nice plant-based alternatives, and a family browsing the web to replace the fridge that just broke might be offered discount appliances and home-delivered take-out. Such solutions would save time and resources on all sides but as argued in the preceding sections, requires responsible use of personal data and accurate algorithms to understand the context the user is in.

There are also trade-offs between rule-based and AI-based automation. Rule-based automation offers the advantage of higher transparency by relying more on human decision-making and domain expertise. Advertisers can rely on their knowledge and insights to make strategic decisions, ensuring that ad campaigns align with their brand values and objectives. Rule-based automation also allow for greater control and customization, as advertisers can make brand-aligned adjustments based on performance feedback and market conditions.

On the other hand, AI-based automation offers scalability and efficiency. AI algorithms can process vast amounts of data and make real-time optimizations to deliver highly targeted and relevant ads to specific audience segments. They can identify patterns and trends that humans may overlook, leading to more effective campaign outcomes. However, AI-based automation may lack the creativity and nuanced decision-making that humans bring to the table. There is also a risk of algorithmic biases and unintended consequences, as AI algorithms rely on historical data and patterns that may perpetuate existing biases. On the other hand, the rules behind rule-based automation may also be biased or lead to biased outcomes.

We expect that personalized targeting (or using a combination of both personal and contextual data) and AI-based automation are the default strategies for many advertisers today, and will become even more so in the future. This is, in many cases, an attractive strategy to pursue, but it incurs risks as well. Personalized targeting is seen as highly effective but requires access to sensitive data, which is associated with more risks concerning personal integrity and algorithmic bias. It is possible to work with personalized targeting in a responsible manner, but places higher demands on the advertiser both when setting up ad campaigns and evaluating their performance.

We also recognize that it is tempting to try and automate as much as possible, as AI-driven implementations are “easy” and take care of themselves. But it is important to confirm that the organization has access to expertise: legal to ensure adherence to applicable regulations, and technical to ascertain understanding of what the system is doing. Because AI-based systems often lack explainability (i.e., we do not know what happens and if this is good or bad), their actions can lead to unforeseen consequences (i.e., potentially leading to discriminatory outcomes or brand reputational risks), and might even lead to suboptimal performance (i.e., will most likely work, but could be even better if we tweak the AI’s suggested solution). Whichever advertising strategy is pursued, it is crucial to test AI systems, both prior to initial use and at regular intervals thereafter, to ensure it does not exhibit discrimination based on factors like race, gender, or other protected characteristics.

In the end, it boils down to how large investments firms are willing to make and how much risk they are willing to incur while adhering to current legislation. Access to more data and expertise gives firms more freedom to choose among different ad strategies. Without data, they are pushed towards contextual targeting. Without domain expertise, they are pushed towards AI-based automation. However, we notice an interesting paradox with regards to expertise and automation: rule-based automation might seem as if it requires more expertise compared to AI-based automation (as more decisions are made by humans), why many might gravitate towards the "easy" AI-based solutions which promise to handle some of the work for you, but without other types of expertise (legal, technical, etc.) advertisers should be wary of jumping on the AI bandwagon; there are complex and strategic risks to consider. We understand and encourage marketers to experiment with AI, testing and finding ways to incorporate it into their advertising workflows, but agree with other researchers that they should do so in a responsible manner and with caution (Sands et al., 2024).

With both data and expertise, an advertiser can combine targeting approaches (e.g., combination of contextual and personalized data), understand when to rely on AI to make decisions, (e.g., low-risk situations), and when to do it themselves (e.g., high-risk situations or special cases where domain knowledge is key). This flexibility and knowledge allow advertisers to execute effective ad campaigns, all the while making informed and ethical decisions, which adhere to current legislation.

Conclusion

Programmatic advertising presents both opportunities and challenges for advertisers. Access to more data and competences give advertisers more freedom to choose among different ad strategies. Without personal data, advertisers are left with contextual targeting. Having access to such data but without technological competence, advertisers are often pushed towards solutions involving AI almost by default, feeding it as much as data as possible, both personal and contextual. With access to data and competence, advertisers can strive for powerful ad strategies combining elements from all parts of the conceptual framework, playing to the strengths of each: contextual and personalized targeting, using either rule-based or AI-based automation. And when combinations are not possible, advertisers will at least be able to make informed choices of which strategy to pursue when.

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References

Åbonde Garke, A., Söndergaard, M., & Modig, E. (2021). Always-On Eye Tracking Reveals Problems with Financing News Websites Through Advertising. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3949327

Adam, M., & Hocquard, C. (2023). *Artificial intelligence, democracy and elections* (PE 751.478). European Parliamentary Research Service.

Aguirre, E., Mahr, D., Grewal, D., de Ruyter, K., & Wetzels, M. (2015). Unraveling the Personalization Paradox: The Effect of Information Collection and Trust-Building Strategies on Online Advertisement Effectiveness. *Journal of Retailing*, *91*(1), 34–49. https://doi.org/10.1016/j.jretai.2014.09.005

Ahrens, J., & Coyle, J. R. (2011). A Content Analysis of Registration Processes on Websites: How Advertisers Gather Information to Customize Marketing Communications. *Journal of Interactive Advertising*, *11*(2), 12–26. https://doi.org/10.1080/15252019.2011.10722181

Aiolfi, S., Bellini, S., & Grandi, B. (2022). Using mobile while shopping in-store: A new model of impulse-buying behaviour. *Journal of Consumer Marketing*, *39*(5), 432–444. https://doi.org/10.1108/JCM-05-2020-3823

Alaimo, C., & Kallinikos, J. (2018). Objects, Metrics and Practices: An Inquiry into the Programmatic Advertising Ecosystem. In U. Schultze, M. Aanestad, M. Mähring, C. Østerlund, & K. Riemer (Eds.), *Living with Monsters? Social Implications of*

Algorithmic Phenomena, Hybrid Agency, and the Performativity of Technology (pp. 110–123). Springer International Publishing. https://doi.org/10.1007/978-3-030-04091-8_9

Ali, M., Sapiezynski, P., Bogen, M., Korolova, A., Mislove, A., & Rieke, A. (2019). Discrimination through optimization: How Facebook's ad delivery can lead to skewed outcomes. *Proceedings of the ACM on Human-Computer Interaction*, *3*(CSCW), 1–30. https://doi.org/10.1145/3359301

Amankwah-Amoah, J., Abdalla, S., Mogaji, E., Elbanna, A., & Dwivedi, Y. K. (2024). The impending disruption of creative industries by generative AI: Opportunities, challenges, and research agenda. *International Journal of Information Management*, *79*, 102759. https://doi.org/10.1016/j.ijinfomgt.2024.102759

Aridor, G., Che, Y.-K., Nelson, W., & Salz, T. (2020). The Economic Consequences of Data Privacy Regulation: Empirical Evidence from GDPR. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3522845

Arora, N., Ensslen, D., Fiedler, L., Liu, W. W., Robinson, K., Stein, E., & Schüler, G. (2021). *The value of getting personalization right—Or wrong—Is multiplying* (Next in Personalization 2021 Report). McKinsey & Company. https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/the-value-of-getting-personalization-right-or-wrong-is-multiplying

ASA. (2023). *Generative AI & Advertising: Decoding AI Regulation*. Advertising Standards Authority. https://www.asa.org.uk/news/generative-ai-advertising-decoding-ai-regulation.html

Atleson, M. (2023, May 1). *The Luring Test: AI and the engineering of consumer trust*. Federal Trade Commission. https://www.ftc.gov/business-guidance/blog/2023/05/luring-test-ai-engineering-consumer-trust

Baek, T. H., Kim, J., & Kim, J. H. (2024). Effect of disclosing AI-generated content on prosocial advertising evaluation. *International Journal of Advertising*, 1–22. https://doi.org/10.1080/02650487.2024.2401319

Bar-Tal, O., Chefer, H., Tov, O., Herrmann, C., Paiss, R., Zada, S., Ephrat, A., Hur, J., Liu, G., Raj, A., Li, Y., Rubinstein, M., Michaeli, T., Wang, O., Sun, D., Dekel, T., & Mosseri, I. (2024). *Lumiere: A Space-Time Diffusion Model for Video Generation* (arXiv:2401.12945). arXiv. https://doi.org/10.48550/arXiv.2401.12945

Basis Technologies. (2023, August 18). *Everything You Need to Know About Programmatic In-Housing—Basis Technologies*. https://basis.com/blog/everything-you-need-to-know-about-programmatic-in-housing/

Berghel, H. (2018). Malice Domestic: The Cambridge Analytica Dystopia. *Computer*, *51*(5), 84–89. https://doi.org/10.1109/MC.2018.2381135

Betker, J., Goh, G., Jing, L., Brooks, T., Wang, J., Li, L., Ouyang, L., Zhuang, J., Lee, J., Guo, Y., Manassra, W., Dhariwal, P., Chu, C., Jiao, Y., & Ramesh, A. (2023). *Improving image generation with better captions*. https://cdn.openai.com/papers/dall-e-3.pdf

Bleier, A. (2021). On the Viability of Contextual Advertising as a Privacy-Preserving Alternative to Behavioral Advertising on the Web. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3980001

Bleier, A., & Eisenbeiss, M. (2015a). Personalized Online Advertising Effectiveness: The Interplay of What, When, and Where. *Marketing Science*, *34*(5), 669–688. https://doi.org/10.1287/mksc.2015.0930

Bleier, A., & Eisenbeiss, M. (2015b). The Importance of Trust for Personalized Online Advertising. *Journal of Retailing*, *91*(3), 390–409. https://doi.org/10.1016/j.jretai.2015.04.001

Boerman, S. C., Kruikemeier, S., & Bol, N. (2021). When is personalized advertising crossing personal boundaries? How type of information, data sharing, and personalized pricing influence consumer perceptions of personalized advertising. *Computers in Human Behavior Reports*, *4*, 100144. https://doi.org/10.1016/j.chbr.2021.100144

Boerman, S. C., Kruikemeier, S., & Zuiderveen Borgesius, F. J. (2017). Online Behavioral Advertising: A Literature Review and Research Agenda. *Journal of Advertising*, *46*(3), 363–376. https://doi.org/10.1080/00913367.2017.1339368

Boudet, J., Gregg, B., Rathje, K., Stein, E., & Vollhardt, K. (2019, June 18). *The future of personalization—And how to get ready for it*. McKinsey & Company. https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/the-future-of-personalization-and-how-to-get-ready-for-it

Brodherson, M., Broitman, A., Macdonald, C., & Royaux, S. (2023, April 21). *The demise of third-party cookies and identifiers | McKinsey*. McKinsey & Company. https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/the-demise-of-third-party-cookies-and-identifiers#/

Brooks, T., Peebles, B., Holmes, C., DePue, W., Guo, Y., Jing, L., Schnurr, D., Taylor, J., Luhman, T., Luhman, E., Ng, C., Wang, R., & Ramesh, A. (2024). *Video generation models as world simulators*. https://openai.com/research/video-generation-models-as-world-simulators

Broussard, G. & IAB. (2018). *Programmatic In-Housing: Benefits, Challenges and Key Steps to Building Internal Capabilities*. Interactive Advertising Bureau. https://www.iab.com/wp-content/uploads/2018/05/IAB_Programmatic-In-Housing-Whitepaper_v5.pdf

Byrd, A. (2023, June 16). *The State of Programmatic Advertising in 2023*. AdMonsters. https://www.admonsters.com/the-state-of-programmatic-advertising-in-2023/

Cai, H., Ren, K., Zhang, W., Malialis, K., Wang, J., Yu, Y., & Guo, D. (2017). Real-Time Bidding by Reinforcement Learning in Display Advertising. *Proceedings of the Tenth ACM International Conference on Web Search and Data Mining*, 661–670. https://doi.org/10.1145/3018661.3018702

Chen, G., Xie, P., Dong, J., & Wang, T. (2019). Understanding Programmatic Creative: The Role of AI. *Journal of Advertising*, *48*(4), 347–355. https://doi.org/10.1080/00913367.2019.1654421

Choi, H., Mela, C. F., Balseiro, S. R., & Leary, A. (2020). Online Display Advertising Markets: A Literature Review and Future Directions. *Information Systems Research*, *31*(2), 556–575. https://doi.org/10.1287/isre.2019.0902

Choi, J.-A., & Lim, K. (2020). Identifying machine learning techniques for classification of target advertising. *ICT Express*, *6*(3), 175–180. https://doi.org/10.1016/j.icte.2020.04.012

Corrêa, A. M. (2022). Regulating targeted advertising: Addressing discrimination with transparency, fairness, and auditing tests remedies. *Computer Law & Security Review*, *46*, 105732. https://doi.org/10.1016/j.clsr.2022.105732

De Keyzer, F., Dens, N., & De Pelsmacker, P. (2022). How and When Personalized Advertising Leads to Brand Attitude, Click, and WOM Intention. *Journal of Advertising*, *51*(1), 39–56. https://doi.org/10.1080/00913367.2021.1888339

Dutton, S., & White, S. (2021, May 18). *What is the Privacy Sandbox?* Chrome for Developers. https://developer.chrome.com/docs/privacy-sandbox/overview/

European Commission. (2023, April 25). *Questions and Answers: Digital Services Act* [Text]. European Commission - European Commission. https://ec.europa.eu/commission/presscorner/detail/en/QANDA_20_2348

European Parliament. (2023, June 14). *EU AI Act: First regulation on artificial intelligence | News | European Parliament*. https://www.europarl.europa.eu/news/en/headlines/society/20230601STO93804/eu-ai-act-first-regulation-on-artificial-intelligence

Fair, L. (2022, December 19). *$245 million FTC settlement alleges Fortnite owner Epic Games used digital dark patterns to charge players for unwanted in-game purchases*. Federal Trade Commission. https://www.ftc.gov/business-guidance/blog/2022/12/245-million-ftc-settlement-alleges-fortnite-owner-epic-games-used-digital-dark-patterns-charge

Figas, N. (2023, March 15). *Zero-Party, First-Party and Third-Party Data: What's the Difference?* Clearcode | Custom AdTech and MarTech Development. https://clearcode.cc/blog/zero-first-third-party-data-comparision/

Gemini Team, Anil, R., Borgeaud, S., Wu, Y., Alayrac, J.-B., Yu, J., Soricut, R., Schalkwyk, J., Dai, A. M., Hauth, A., Millican, K., Silver, D., Petrov, S., Johnson, M., Antonoglou, I., Schrittwieser, J., Glaese, A., Chen, J., Pitler, E., … Vinyals, O. (2023). *Gemini: A Family of Highly Capable Multimodal Models* (arXiv:2312.11805). arXiv. https://doi.org/10.48550/arXiv.2312.11805

Ghose, A., Kwon, H. E., Lee, D., & Oh, W. (2019). Seizing the Commuting Moment: Contextual Targeting Based on Mobile Transportation Apps. *Information Systems Research*, *30*(1), 154–174. https://doi.org/10.1287/isre.2018.0792

Gołąb-Andrzejak, E. (2023). The Impact of Generative AI and ChatGPT on Creating Digital Advertising Campaigns. *Cybernetics and Systems*, *0*(0), 1–15. https://doi.org/10.1080/01969722.2023.2296253

Google. (2024). *Personalized and non-personalized ads—Google AdSense Help*. Google. https://support.google.com/adsense/answer/9007336

Greenleaf, G. (2021). *Global Data Privacy Laws 2021: Uncertain Paths for International Standards* (SSRN Scholarly Paper 3836408). https://papers.ssrn.com/abstract=3836408

Häglund, E., & Björklund, J. (2024). AI-Driven Contextual Advertising: Toward Relevant Messaging Without Personal Data. *Journal of Current Issues & Research in Advertising*, *45*(3), 301–319. https://doi.org/10.1080/10641734.2024.2334939

Haleem, A., Javaid, M., Asim Qadri, M., Pratap Singh, R., & Suman, R. (2022). Artificial intelligence (AI) applications for marketing: A literature-based study. *International Journal of Intelligent Networks*, *3*, 119–132. https://doi.org/10.1016/j.ijin.2022.08.005

He, Y., Chen, X., Wu, D., Pan, J., Tan, Q., Yu, C., Xu, J., & Zhu, X. (2021). A Unified Solution to Constrained Bidding in Online Display Advertising. *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, 2993–3001. https://doi.org/10.1145/3447548.3467199

Hicham, N., Nassera, H., & Karim, S. (2023). Strategic Framework for Leveraging Artificial Intelligence in Future Marketing Decision-Making. *Journal of Intelligent Management Decision*, *2*(3), 139–150. https://doi.org/10.56578/jimd020304

Hinton, G. E., Osindero, S., & Teh, Y.-W. (2006). A Fast Learning Algorithm for Deep Belief Nets. *Neural Computation*, *18*(7), 1527–1554. https://doi.org/10.1162/neco.2006.18.7.1527

Jillson, E. (2021, April 19). *Aiming for truth, fairness, and equity in your company's use of AI*. Federal Trade Commission. https://www.ftc.gov/business-guidance/blog/2021/04/aiming-truth-fairness-equity-your-companys-use-ai

Jose, A., & Shetty, S. D. (2022). DistilledCTR: Accurate and scalable CTR prediction model through model distillation. *Expert Systems with Applications*, *193*, 116474. https://doi.org/10.1016/j.eswa.2021.116474

Lambrecht, A., & Tucker, C. (2013). When Does Retargeting Work? Information Specificity in Online Advertising: *Journal of Marketing Research*. https://doi.org/10.1509/jmr.11.0503

Lambrecht, A., & Tucker, C. (2019). Algorithmic Bias? An Empirical Study of Apparent Gender-Based Discrimination in the Display of STEM Career Ads. *Management Science*. https://doi.org/10.1287/mnsc.2018.3093

Li, P., Castelo, N., Katona, Z., & Sarvary, M. (2023). *Determining the Validity of Large Language Models for Automated Perceptual Analysis* (SSRN Scholarly Paper 4241291). https://doi.org/10.2139/ssrn.4241291

Lian, S., Cha, T., & Xu, Y. (2019). Enhancing geotargeting with temporal targeting, behavioral targeting and promotion for comprehensive contextual targeting. *Decision Support Systems*, *117*, 28–37. https://doi.org/10.1016/j.dss.2018.12.004

Lu, X., Zhao, X., & Xue, L. (2016). Is Combining Contextual and Behavioral Targeting Strategies Effective in Online Advertising? *ACM Transactions on Management Information Systems*, *7*(1), 1:1-1:20. https://doi.org/10.1145/2883816

Makridakis, S. (2017). The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. *Futures*, *90*, 46–60. https://doi.org/10.1016/j.futures.2017.03.006

Malthouse, E. C., Maslowska, E., & Franks, J. U. (2018). Understanding programmatic TV advertising. *International Journal of Advertising*, *37*(5), 769–784. https://doi.org/10.1080/02650487.2018.1461733

Minton, E. A., Cornwell, T. B., & Kahle, L. R. (2017). A theoretical review of consumer priming: Prospective theory, retrospective theory, and the affective–behavioral–cognitive model. *Journal of Consumer Behaviour*, *16*(4), 309–321. https://doi.org/10.1002/cb.1624

Morgan, B. (2020, February 18). 50 Stats Showing The Power Of Personalization. *Forbes*. https://www.forbes.com/sites/blakemorgan/2020/02/18/50-stats-showing-the-power-of-personalization/

Neumann, N., Tucker, C. E., & Whitfield, T. (2019). Frontiers: How Effective Is Third-Party Consumer Profiling? Evidence from Field Studies. *Marketing Science*, *38*(6), 918–926. https://doi.org/10.1287/mksc.2019.1188

OpenAI. (2022, November 30). *Introducing ChatGPT*. https://openai.com/blog/chatgpt

Perlich, C., Dalessandro, B., Hook, R., Stitelman, O., Raeder, T., & Provost, F. (2012). Bid optimizing and inventory scoring in targeted online advertising. *Proceedings of the 18th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 804–812. https://doi.org/10.1145/2339530.2339655

Qin, X., & Jiang, Z. (2019). The Impact of AI on the Advertising Process: The Chinese Experience. *Journal of Advertising*, *48*(4), 338–346. https://doi.org/10.1080/00913367.2019.1652122

Rodgers, Z. (2017, June 20). *Cannes Q&A: New York Times CEO Calls For Ad Tech Reform*. AdExchanger. https://www.adexchanger.com/publishers/new-york-times-ceo-inveighs-skeefo-ad-tech-despite-recent-strides/

Roth, E. (2023, September 25). *Facebook can be sued over biased ad algorithm, says court*. The Verge. https://www.theverge.com/2023/9/25/23889747/facebook-biased-ad-algorithm-aclu-court

Sahni, N. S., Narayanan, S., & Kalyanam, K. (2019). An Experimental Investigation of the Effects of Retargeted Advertising: The Role of Frequency and Timing. *Journal of Marketing Research*, *56*(3), 401–418. https://doi.org/10.1177/0022243718813987

Sahni, N. S., Wheeler, S. C., & Chintagunta, P. (2018). Personalization in Email Marketing: The Role of Noninformative Advertising Content. *Marketing Science*, *37*(2), 236–258. https://doi.org/10.1287/mksc.2017.1066

Salkowitz, R. (2022, September 16). Midjourney Founder David Holz On The Impact Of AI On Art, Imagination And The Creative Economy. *Forbes*. https://www.forbes.com/sites/robsalkowitz/2022/09/16/midjourney-founder-david-holz-on-the-impact-of-ai-on-art-imagination-and-the-creative-economy/

Sands, S., Campbell, C., Ferraro, C., Demsar, V., Rosengren, S., & Farrell, J. (2024). Principles for advertising responsibly using generative AI. *Organizational Dynamics*, *53*(2), 101042. https://doi.org/10.1016/j.orgdyn.2024.101042

Schäfer, A., & Weiss, O. (2016). Understanding Demand-Side-Platforms. In O. Busch (Ed.), *Programmatic Advertising* (pp. 75–86). Springer International Publishing. https://doi.org/10.1007/978-3-319-25023-6_6

Shumanov, M., Cooper, H., & Ewing, M. (2022). Using AI predicted personality to enhance advertising effectiveness. *European Journal of Marketing*, *56*(6), 1590–1609. https://doi.org/10.1108/EJM-12-2019-0941

Silvennoinen, J. M., & Jokinen, J. P. P. (2016). Appraisals of Salient Visual Elements in Web Page Design. *Advances in Human-Computer Interaction*, *2016*, e3676704. https://doi.org/10.1155/2016/3676704

Smith, A. (2020, April 8). *Using Artificial Intelligence and Algorithms*. Federal Trade Commission. https://www.ftc.gov/business-guidance/blog/2020/04/using-artificial-intelligence-and-algorithms

Spataro, J. (2023, March 16). *Introducing Microsoft 365 Copilot – your copilot for work*. The Official Microsoft Blog. https://blogs.microsoft.com/blog/2023/03/16/introducing-microsoft-365-copilot-your-copilot-for-work/

Speicher, T., Ali, M., Venkatadri, G., Ribeiro, F. N., Arvanitakis, G., Benevenuto, F., Gummadi, K. P., Loiseau, P., & Mislove, A. (2018). Potential for Discrimination in Online Targeted Advertising. In S. A. Friedler & C. Wilson (Eds.), *Proceedings of the 1st Conference on Fairness, Accountability and Transparency* (Vol. 81, pp. 5–19). PMLR. https://proceedings.mlr.press/v81/speicher18a.html

Statista. (2024a, February 12). *Global programmatic advertising spending from 2017 to 2028*. Statista. https://www.statista.com/statistics/275806/programmatic-spending-worldwide/

Statista. (2024b, October 29). *Programmatic share in global digital ad spend from 2021 to 2030*. Statista. https://www.statista.com/forecasts/1316147/programmatic-share-digital-ad-spend-worldwide

Sweeney, L. (2013). Discrimination in Online Ad Delivery. *Queue*, *11*(3), 10. https://doi.org/10.1145/2460276.2460278

Sweeney, M. (2020, November). *AdTech/MarTech Development Teams: In-House vs Outsourcing vs Development Partner*. Clearcode | Custom AdTech and MarTech Development. https://clearcode.cc/blog/adtech-martech-development-partner/

Sweeney, M. (2023, January 23). *6 Alternatives to Third-Party Cookies and Mobile IDs in AdTech*. Clearcode | Custom AdTech and MarTech Development. https://clearcode.cc/blog/alternatives-third-party-cookies-mobile-ids/

The Economist. (2023, September 18). Could OpenAI be the next tech giant? *The Economist*. https://www.economist.com/business/2023/09/18/could-openai-be-the-next-tech-giant

Tucker, C. E. (2014). Social Networks, Personalized Advertising, and Privacy Controls. *Journal of Marketing Research*, *51*(5), 546–562. https://doi.org/10.1509/jmr.10.0355

Turow, J., King, J., Hoofnagle, C. J., Bleakley, A., & Hennessy, M. (2009). *Americans Reject Tailored Advertising and Three Activities that Enable It* (SSRN Scholarly Paper 1478214). https://doi.org/10.2139/ssrn.1478214

Varnali, K. (2021). Online behavioral advertising: An integrative review. *Journal of Marketing Communications*, *27*(1), 93–114. https://doi.org/10.1080/13527266.2019.1630664

Wang, H., Liu, N., Zhang, Y., Feng, D., Huang, F., Li, D., & Zhang, Y. (2020). Deep reinforcement learning: A survey. *Frontiers of Information Technology & Electronic Engineering*, *21*(12), 1726–1744. https://doi.org/10.1631/FITEE.1900533

Wedel, M., & Kamakura, W. A. (2000). *Market Segmentation* (Vol. 8). Springer US. https://doi.org/10.1007/978-1-4615-4651-1

Wojdynski, B. W., & Bang, H. (2016). Distraction effects of contextual advertising on online news processing: An eye-tracking study. *Behaviour & Information Technology*, *35*(8), 654–664. https://doi.org/10.1080/0144929X.2016.1177115

Wu, L., Dodoo, N. A., & Wen, T. J. (2024). Disclosing AI's Involvement in Advertising to Consumers: A Task-Dependent Perspective. *Journal of Advertising*, 1–19. https://doi.org/10.1080/00913367.2024.2309929

Wylie, C. (2019). *Mindf*ck: Cambridge Analytica and the plot to break America* (First edition). Random House.

Yankelovich, D., & Meer, D. (2006). Rediscovering market segmentation. *Harvard Business Review*, *84*(2), 122–131. Business Source Ultimate.

Yi, Y. (1991). The Influence of Contextual Priming on Advertising Effects. *Advances in Consumer Research*, *18*(1), 417–425. Business Source Ultimate.

Yun, J. T., Segijn, C. M., Pearson, S., Malthouse, E. C., Konstan, J. A., & Shankar, V. (2020). Challenges and Future Directions of Computational Advertising Measurement Systems. *Journal of Advertising*, *49*(4), 446–458. https://doi.org/10.1080/00913367.2020.1795757

Zawadziński, M., & Sweeney, M. (2019, May 9). *Google Chrome To Kill Off Third-Party Cookies: What It Means for AdTech*. Clearcode | Custom AdTech and MarTech Development. https://clearcode.cc/blog/chrome-impact-adtech/

Zhang, W., Yuan, S., & Wang, J. (2014). Optimal real-time bidding for display advertising. *Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 1077–1086. https://doi.org/10.1145/2623330.2623633

Zhao, X., Gu, C., Zhang, H., Yang, X., Liu, X., Tang, J., & Liu, H. (2021). DEAR: Deep Reinforcement Learning for Online Advertising Impression in Recommender Systems. *Proceedings of the AAAI Conference on Artificial Intelligence*, *35*(1), 750–758. https://doi.org/10.1609/aaai.v35i1.16156

Zhu, Y., & Wilbur, K. C. (2011). Hybrid Advertising Auctions. *Marketing Science*, *30*(2), 249–273. https://doi.org/10.1287/mksc.1100.0609

Zuiderveen Borgesius, F. J. (2015). Personal data processing for behavioural targeting: Which legal basis? *International Data Privacy Law*, *5*(3), 163–176. https://doi.org/10.1093/idpl/ipv011