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THE IMPACT OF COOKIE REGIME CHANGE ON THE EFFECTIVENESS OF AUTOMATIC RETARGETING IN ADVERTISING

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Abstract

The constantly evolving legislation concerning the usage of cookies raises many concerns about the effectiveness of targeted online advertisements. Retargeting represents an advanced targeting strategy requiring detailed user data and thus may be potentially highly sensitive to cookie restrictions. The retargeting effectiveness is tested in terms of type (standard, dynamic), advertising platform (Meta Ads, Google Ads), and the ad performance development in time. The data were collected through a Czech home goods online retailer. This paper tests the effectiveness of 432 retargeting ads collected during the opt-out cookie regime by comparing them with 432 retargeting ads collected after the transition to the opt-in cookie regime. The study created 216 ads on Google and 216 ads on Facebook. The entire experiment took one month to be implemented in 2021 and repeated in precisely the same manner in 2022. After this period, data were processed with SPSS Statistics. Both Facebook and Google (Conversion Lift) provide A/B testing tools. The results suggest that standard retargeting ads are more effective in utilitarian browsing. In contrast, dynamic retargeting is more successful in reaching users in the hedonic environment of social networks. Moreover, the performance of retargeting ads evolves in the different stages along the customer journey. There are differences in the total number of tracked users in terms of the transition from the opt-out to the opt-in cookie regime. However, the performance of programmatic advertising appears moderately affected.

Keywords marketing automation, online advertising, Google Ads, Meta Ads, cookie tracking, opt-in regime, opt-out regime, Czech Republic

JEL Classification M37, M38, M39

INTRODUCTION

Online engagement optimization by content personalization using individual user preferences and online privacy concerns related to advanced targeting techniques are two sides of the current electronic commerce environment (Todri, 2022). Behavioral advertising aims to study the characteristics of Internet users through their actions to deduce their profile and offer them adapted advertisements. As a result, two users visiting the same web page may receive different types of ads (Zhou, 2020; Varnali, 2021). Performing the analysis inherent in the functioning of a behavioral advertisement requires a significant amount of information, such as the nature of the websites visited, the frequency of these visits, the time spent, the interactions which took place, the purchases which were made, or the keywords which were entered in the search engine (Blomster & Koivumäki, 2022). This need for information collection and processing has inspired various advertising platforms to diversify their services and activities to follow Internet users even more closely and, ultimately, to draw the most detailed possible portrait of their behavior.

Conflict of interest statement:
Author(s) reported no conflict of interest

Advertising platforms like Meta (formerly Facebook) and Google have constantly improved their advertising tools to provide users with the most personalized content possible. Recently, platforms witnessed the introduction of new functionalities based on machine learning and artificial intelligence, allowing advertisers to create automatized or semi-automatized ads with dynamically changing content (Villas-Boas & Yao, 2021; Boerman et al., 2017). Standard retargeting and dynamic retargeting are the latest examples of this marketing automation category, promising the highest level of personalization.

However, due to the turbulent changes regarding online privacy and cookie tracking restrictions, programmatic advertising faces significant challenges (Masood et al., 2022; Sakamoto & Matsunaga, 2019). Therefore, although providing the highest level of ad personalization, standard and dynamic retargeting may be affected by the decreased level of information collected. The importance of user data for programmatic advertising has been stressed multiple times, even more since cookie tracking became a pressing issue.

1. LITERATURE REVIEW

Lead management (Ohiomah et al., 2019), AIDA (Strong, 1925), and TOFU-MOFU-BOFU (Steinbach et al., 2015) models represent the conceptual basis of modern marketing and eCommerce automation (Meta, n.d.a; Berman, 2018). Goeldner (1962) first introduced the term marketing automation. By analyzing the data users leave behind when browsing the online environment, he wanted to optimize the entire user experience of shopping for products online. According to Bucklin et al.'s definition (1998) of the marketing automation framework, data are a critical part of marketing automation. All subsequent processes are closely linked to their quantity and quality. Marketing automation represents a key mechanism for programmatic advertising platforms and, thus, also the collection of data about their users. Both the advertising platforms, Meta Ads and Google Ads, use their specific methods of user tracking, user targeting, and content personalization, which may consequently influence the performance of the ad campaigns (Meta, n.d.a; Semerádová & Weinlich, 2020a, 2020b; Berman, 2018).

HTTP cookies technology (from now on referred to as cookies) is currently necessary for most tracking, analytical, and advertising systems on the Internet (Thomas, 2018). In the case of Google Ads, the data collection process begins with the user's visit to the website. The code uses data stored in the browser to find out where a visitor came from, what operating system he is working on, the type of browser, and multiple other settings. After finding this information, the tracking code creates or updates cookies on the visitor's computer (Google, n.d.a). Google Analytics and other Google applications use custom cookies to determine which domain to measure and distinguish unique users, remember the number and time of previous visits, remember traffic source information, and many other custom variables (Google, n.d.b; Vecchione et al., 2016).

Similarly, a Meta pixel (formerly Facebook pixel) is a piece of javascript code that, when paired with a website or e-shop, helps with optimizing, measuring, and compiling advertising campaigns on Facebook and Instagram's social networks. Meta pixel uses two primary functions to categorize the collected data – audiences and events. Audiences represent users divided based on set criteria, such as demographic data or age (interactions with websites and content). Events describe the user's activities with the website, such as subscribing to the newsletter, adding goods to the cart, visiting the landing page, downloading the e-book, and sending the form (Meta, n.d.b).

Although the Google tracking code and Meta pixel share similar goals, they may perform differently due to the different data the advertising platforms collect and the ad placement contexts. While Meta Ads focus on user identification concerning their accounts and behavioral patterns on Facebook, Instagram, and other Meta applications, Google Ads use a browser and keyword search- related information instead (Semerádová & Weinlich, 2020b). The data collection process about website conversions in both cases, for Meta Ads and Google Ads, can occur if a visi-

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tor's browser accepts cookies. However, not all advertising data comes from cookies. For instance, Facebook and Instagram have internal tracking mechanisms allowing them to classify users into similar targeting audiences based on their preferences and behavior (Semerádová & Weinlich, 2019). Therefore, the targeting effectiveness of advertising networks may not be significantly affected by the cookie restrictions, even though the conversion tracking ability is. The cookie tracking dilemma thus makes many advertisers question the current effectiveness of programmatic advertising.

Retargeting is a method that targets those consumers who have already made a previous interaction with the brand and can therefore be expected to be of interest to a consumer (Jiang et al., 2020). This group of users represents a higher value for the advertiser, as they have already demonstrated a possible interest in the offered product or service. To convert users to customers, retargeting through personalized and highly relevant ads reminds the users of the brand and attracts them back to the website to perform the first, repeated, or complete conversion (Cooper et al., 2023).

Currently, two types of retargeting are available – standard and dynamic (Meta, n.d.c; Google, n.d.c, n.d.d). Standard retargeting represents a less personalized form of retargeting and consists in addressing a group of users (an audience) in the same stage of the shopping process with the same content (Figure 1) (Lambrecht & Tucker, 2013).

Advertisers can do so with dynamic visuals if they want to intensify personalization. Dynamic retargeting ads use content generated based on what consumers have shown interest in in the past (products displayed or added to cart). In addition, dynamic retargeting allows an advertiser to change parts of an ad, such as an image, price, product description, or call to action. These options increase the chances of conversion and a shorter purchasing process (Google, n.d.e). However, to use the dynamic retargeting strategies, the advertisers must first upload a product feed with all the variables that will dynamically change in the ads (Figure 2). The advertising platform then uses information from this feed to generate custom parts of the ads, which are then displayed to the users from one audience, who may have different preferences as individuals (Meta, n.d.c; Google, n.d.d, 2022e).

Retargeting is part of behavioral marketing that brings high profitability (Jiang et al., 2021). Saleh (n.d.) states that three out of four consumers now notice retargeted ads. However, Saleh (n.d.) also mentions the counteracting effect of privacy concerns that may affect user reactiveness toward highly personalized ads. In his white paper, he mentions that 18.78% of the respondents are very concerned when confronted with retargeting ads that follow them once they leave the website, 34.8% are somewhat concerned, and 29.41% are neither concerned nor unconcerned.

According to Tucker (2014), potential customers may perceive targeted, relevant advertising as an-

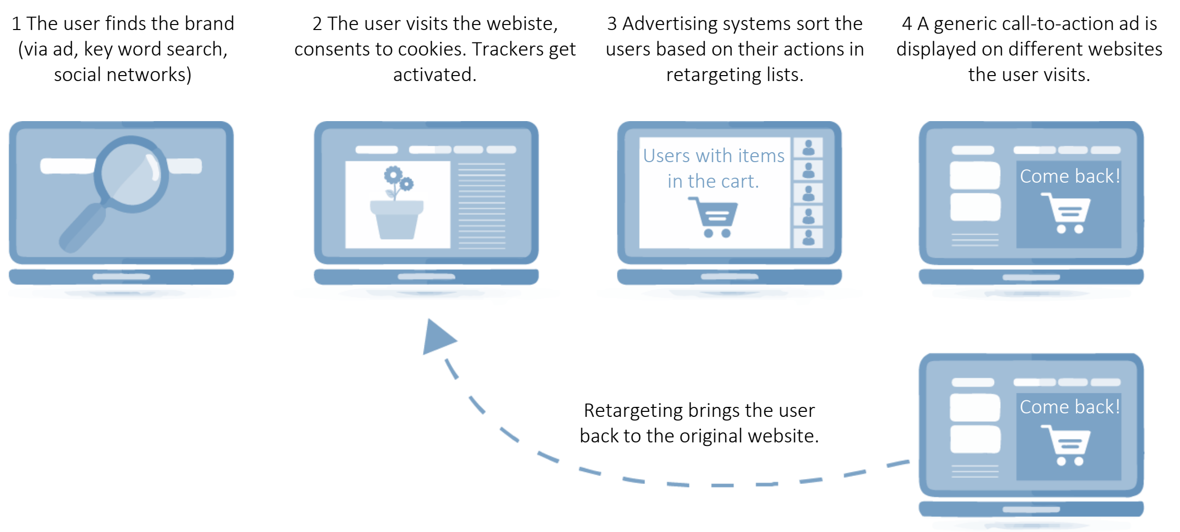

Figure 1. Standard retargeting mechanism in advertising

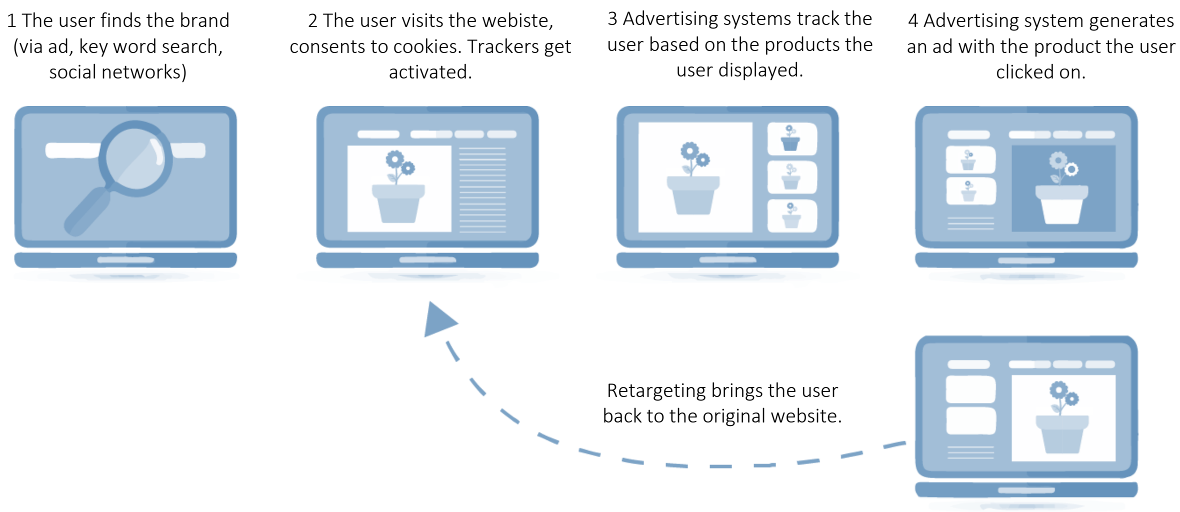

Figure 2. Dynamic retargeting mechanism in advertising

noying to scary and feel that someone is watching them. This can lead to a less positive attitude toward the product and question the brand's credibility. As White et al. (2008) claim, "retargeting is risky because users may feel watched and limited." They can take this as an invasion of privacy and reject personalized advertising accordingly. King and Jessen (2010) agree that great personalization can lead to privacy and personal data protection concerns for consumers.

Contradictory, Kim and Ohk (2017) surveyed 258 respondents to examine the positive and negative impacts caused by retargeting. The results suggest that retargeting evokes positive emotions in potential customers. Therefore, retargeting positively impacts a potential customer only if the retargeting advertisement is done correctly. On the other hand, if the quality of retargeting is inferior, it negatively affects the perception of the company's brand and evokes negative emotions in consumers. The same happens with over-displaying banner ads because excessive retargeting can create a sense of pressure and distrust in a potential customer.

Bleier and Eisenbeiss (2015) experimented with a fashion and sporting goods retailer e-shop that contained more than 30,000 products in more than 180 categories and nearly 600 brands. According to their results, personalization significantly affects the click-through rate, and personalized banners are most effective during the first few days of retargeting but quickly lose effectiveness. Furthermore, the cumulative effect of personalized banners decreases significantly over time compared to non-personalized banners. This phenomenon is called hyper-personalization (Bleier & Eisenbeiss, 2015).

According to Sahni et al. (2019), retargeting causes potential customers to return to the advertised website by 14.6% during the first four weeks of targeting. In the first week of targeting, retargeting efficiency is 33%. Furthermore, the experiment outlined evidence of complementarity; if potential customers viewed an advertisement in the first week after viewing the e-shop, retargeting in the second week significantly affected their buying decision. They further state that they did not find evidence that the effect of retargeting decreases with the frequency of displaying the advertised banners.

Lambrecht and Tucker (2013) compared the probability of conversion between standard (generic) and dynamic retargeting. The experiment compared the likelihood of conversion before and after visiting the product review page. Experiment results show that targeting potential customers with dynamic retargeting is not as effective if users have not seen product reviews yet. Therefore, if potential customers have yet to visit the product review page, targeting them with standard retargeting is better. In contrast, users who have read reviews of a previously viewed product respond better to dynamic than standard retargeting.

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The previous findings on programmatic advertising and retargeting suggest that the effectiveness of retargeting may change over time (Kim & Ohk, 2017; Sahni et al., 2019). There is also a probability of different performance of standard and dynamic retargeting due to the level of ad personalization and privacy concerns (Su et al., 2016).

The European Union has long been aware of the potential conflicts of cookie tracking with the protection of the privacy of Internet users. It has therefore addressed this issue in Directive 2002/58/EC of July 12, 2002, on privacy and electronic communications (the "ePrivacy Directive") (European Parliament & Council of the European Union, 2002). Regarding consent to their storage, the European legislators first introduce an opt-out regime, i.e., a user must be able to refuse the storage of cookies on his device. The later amendment of the ePrivacy Directive by Directive 2009/136/EC of November 25, 2009, changed this approach to opt-in (European Parliament & Council of the European Union, 2009).

However, the Czech legislators carried out the implementation inconsistently, failing to consider the amendment to ePrivacy Directive No. 2009/136 / EC and the Czech Act. No. 127/2005 Coll. on electronic communications allowed to keep using the opt-out regime (Ministry of Industry and Trade of the Czech Republic, 2005). With the beginning of 2022, the rules for operating virtually all websites have fundamentally changed. The existing more freely set principles were considerably tightened, and the new opt-in regime applies from January 1, 2022. The user's previous presumed consent to process cookies is no longer sufficient. Upon arrival on the website, disagreement with the processing of personal data is assumed. It is possible to place and process cookies only after granting active consent. The only exception concerns the technical cookies, which ensure the correct functionality of the website (Hoffmanová & Bešťáková, 2022).

While the opt-out regime had minor practical effects, other than the cookie notification bar (Markou, 2016), the transition to the opt-in regime raises many questions in terms of the effectiveness of programmatic advertising. If users do not actively consent to tracking, no cookies are placed in their browser, and therefore no personalized advertisements will be displayed. It may thus become an issue for advertising platforms to generate dynamic content based on user behavior. In addition, due to the lack of opt-in consent, the advertising platforms will not have the necessary detail of information they need for tools such as retargeting campaigns.

2. AIM AND HYPOTHESES

As the literature review shows, the quality of the input data represents a fundamental prerequisite for the effectiveness of automatized targeted advertising. Advertising performance is affected by the amount of data and the collection method. While automatic retargeting is considered the most effective type of behavioral advertising, it may also be the most sensitive to the undergoing cookie regime changes. The aim of this study is to examine how the performance of retargeting evolves in reaction to the cookie regime change, taking into account the personalization level of the ads (standard, dynamic), advertising platform (Meta Ads, Google Ads), and the ad performance development over time. Therefore, the study elaborates on the following hypotheses:

H1: *Effectiveness of retargeting changes over time.*

H2: *There are performance differences between standard and dynamic retargeting.*

H3: *The transition from an opt-out to an opt-in regime affected the effectiveness of retargeting.*

3. METHOD

The data were collected through a Czech home goods online retailer that sells more than 5,000 products through their website. The product range includes kitchenware, bedding, dishes, cooking and eating utensils, and other decorative home items. The company's websites generate 1,000 visits per day, with a 3:06 average visit duration, 2.84 pages viewed per visit, and a 54.28% bounce rate.

To assess the three research hypotheses, the study created 216 ads on Google and 216 ads on Facebook in 2021, during the cookie opt-out regime and the same distribution of ads sets in 2022, once the new opt-in legislation in the Czech Republic came in-

Table 1. Parameters and numbers of the test campaigns

Parameter	Facebook		Google	
	Standard	Dynamic	Standard	Dynamic
Custom audience	Product feeds 1-36; 91-108	Product feeds 1-36; 91-108	Product feeds 1-36; 91-108	Product feeds 1-36; 91-108
Default audience	Product feeds 37-90	Product feeds 37-90	Product feeds 37-90	Product feeds 37-90
Week 1	Product feeds 37-54	Product feeds 37-54	Product feeds 37-54	Product feeds 37-54
Week 2	Product feeds 55-72	Product feeds 55-72	Product feeds 55-72	Product feeds 55-72
Week 3	Product feeds 73-90	Product feeds 73-90	Product feeds 73-90	Product feeds 73-90
Week 4	Product feeds 1-35; 91-108	Product feeds 91-108	Product feeds 91-108	Product feeds 91-108
Total	108 ads	108 ads	108 ads	108 ads

to force. For each advertising platform, standard and dynamic campaigns were delivered with a default and custom retargeting audience. Since the number of required ads was higher than the average amount of ads managed by the e-shop, the analysis agreed with the owner on splitting the product feed for one of their product categories into multiple sections to avoid an increase in the advertising budget. Therefore, the retargeting ads were set up with 108 different product feeds representing individual products from the same category. Each product feed was used for four types of retargeting ads, standard and dynamic retargeting on Facebook and standard and dynamic retargeting on Google. Also, at least 18 product feeds were used for each parameter observed. A detailed overview of the campaigns and their parameters is displayed in Table 1.

Regarding retargeting audiences, the default audience included users who visited the website last month. However, the custom audience was created with users' actions in mind. Thus, the custom audience included only users who interacted with at least one of the product categories by clicking on the product detail or adding it to the cart. The entire experiment took one month to be implemented in 2021 and repeated in precisely the same manner in 2022. After this period, the Facebook Ads Manager and Google Analytics data were exported, merged into one file, and processed with SPSS Statistics.

The advertiser was unwilling to turn off all other forms of advertising except dynamic remarketing due to a potential income decrease. For this reason, the experiment ran on the assumption that all other forms of advertising are constant, and both exposed users and a control group of users are exposed to these forms of advertising. However, the exposed group of users was targeted by dynamic retargeting, and the control group was not exposed to this type of automatic advertising. Therefore, a series of A/B ad tests were set up, which ran simul-

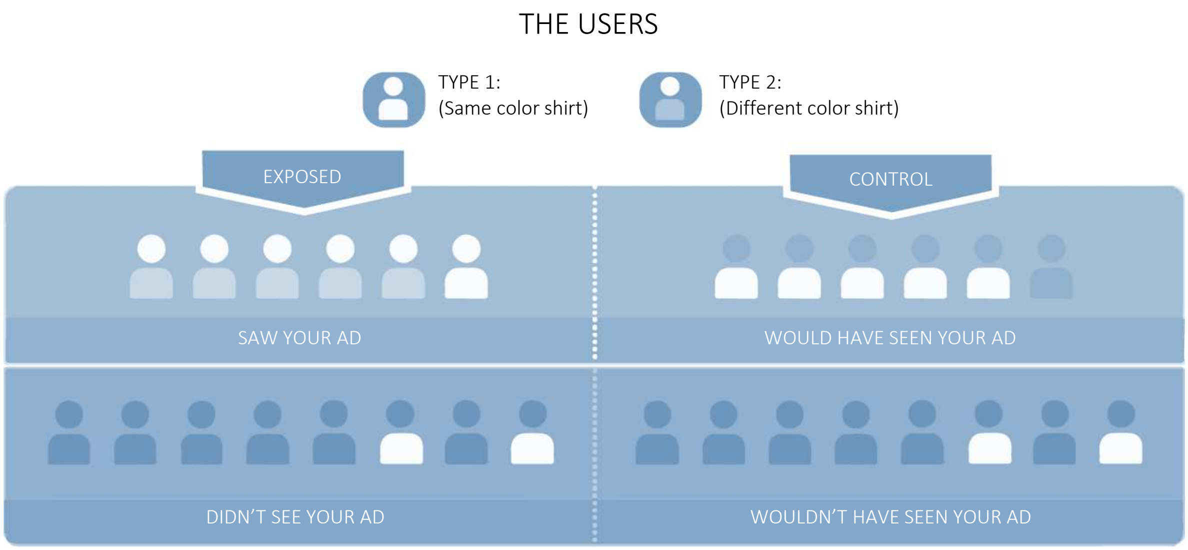

Figure 3. The principle of A/B testing with the Conversion Lift and Facebook

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taneously to avoid external influences and ensure that both groups were exposed to these potential influences simultaneously.

Both Facebook and Google provide A/B testing tools (Figure 3), Google offers a functionality called Conversion Lift. This tool measures the incrementality of campaigns by dividing the audience into exposed and control groups with a ratio of 70:30. The advantage of the Conversion Lift tool is precise control over who can see the ad. An advertising campaign will never reach every user in the target audience. A user's exposure to a particular ad depends on their online behavior, competing advertisers' bids, and targeting parameters. The exposed audience includes users who have seen the ad (type 1) and those who have not seen the advertisement for the above reasons (type 2). The control group is also divided into two. The first half is exposed to Ghost Ads, which means that instead of the advertiser's ad, the users are shown an ad that would win the auction if the advertiser did not compete, meaning the second-best ad with the highest bidding in the auction. The second half of the control group was not exposed to any ad either. The A/B testing functionality Facebook provides uses the same division of the exposed and test groups.

4. RESULTS

The main objective of this analysis was to compare the effectiveness of standard and dynamic retargeting. The data exported from Meta and Google Ads were divided for each evaluation based on the parameters observed: retargeting type (standard retargeting and dynamic retargeting), platform (Meta and Google), and the year of data collection (2021 and 2022). The study ran a series of paired T-tests to evaluate research hypotheses, except for H1, where a graphical representation of performance development in time was used. The summary statistics for the two data sets (2021 and 2022) are represented in Tables 2 and 3. The performance of the campaigns was examined based on the following metrics:

- number of views (measured as the number of ad impressions);
- number of clicks (measured as the number of ad clicks leading to a website visit);
- number of conversions (measured as the number of clicks on the "add to cart" button);
- click/view rate;
- conversion/click rate.

For the paired T-test, the study used aggregated values for the number of views, clicks, and conversions calculated as the sum of the four-week performances per ad. The click/view and conversion/click rates were subsequently calculated from the aggregated values.

To study the retargeting performance development in time (H1), the time records exported from Meta and Google Ads for each observed metric were used and a time series chart to represent the performance trends was created. At each time point (representing a week), the average value was calculated based on the 432 ads (216 for dynamic and 216 for standard retargeting) running at that time (Table 4). As shown in Figure 4, there is a growing trend for the average

Table 2. Summary statistics for the 2021 data set

Performance metrics		N	Min	Max	Mean	Standard Deviation
GOOGLE	Number of views	216	478.00	1007.00	740.18	124.85
	Number of clicks	216	182.00	386.00	287.58	59.13
	Number of conversions	216	68.00	442.00	177.27	68.90
	Click/view rate	216	.23	.61	.40	.09
	Conversion/click rate	216	.33	1.16	.61	.20
META	Number of views	216	512.00	1055.00	775.62	162.38
	Number of clicks	216	181.00	387.00	283.93	60.40
	Number of conversions	216	79.00	388.00	183.40	72.72
	Click/view rate	216	.21	.55	.38	.08
	Conversion/click rate	216	.39	1.47	.65	.22

Table 3. Summary statistics for the 2022 data set

Performance metrics		N	Min	Max	Mean	Standard Deviation
GOOGLE	Number of views	216	286.00	470.00	410.02	51.53
	Number of clicks	216	95.00	177.00	134.53	20.34
	Number of conversions	216	63.00	105.00	85.93	11.80
	Click/view rate	216	.26	.41	.33	.04
	Conversion/click rate	216	.54	.80	.65	.09
META	Number of views	216	272.00	555.00	439.79	54.60
	Number of clicks	216	134.00	199.00	166.53	17.60
	Number of conversions	216	90.00	138.00	109.34	9.08
	Click/view rate	216	.29	.56	.38	.053
	Conversion/click rate	216	.51	1.03	.67	.10

Table 4. Average retargeting performance per week

Week	Average number of views	Average number of clicks	Average number of conversions	Click/view rate (%)	Conversion/click rate (%)
week 1	106.36	50.66	29.51	60.66	47.62
week 2	110.41	54.70	38.89	71.77	49.80
week 3	117.34	28.26	19.76	74.21	23.87
week 4	90.80	16.95	9.66	62.81	19.90

number of clicks, average number of conversions, and conversion/click rate during the first week (50.66, 29.51, 47.62, respectively), which peaks during the second week (54.70, 38.89, 49.80, respectively) and then starts decreasing during the third week (28.26, 29.76, 23.87, respectively). On the other hand, the performance decrease is slighter for the average number of views and the click/view rate. Both advertising metrics peak during the third week (74.21, 23.87, respectively) and then decrease during the fourth week (62.81, 19.90, respectively). Moreover, the click/view rate decrease slope is less steep than the other metrics. Retargeting performance changes over time and may lead to different results based on the length of the campaigns.

Standard and dynamic retargeting use different mechanisms for targeting users and generating advertisements. Moreover, they provide different levels of personalization. Therefore, the paper may also expect differences in their performance (H2). Table 5 compares the paired differences between standard and dynamic retargeting for Meta Ads and Google ads. The results imply that, in terms of the conversion/click rate, standard retargeting brings better results in the context of the Google advertising platform. Contrariwise, in the case of Meta ads, dynamic, more personalized retargeting overperformed standard, more generic retargeting. For standard and dynamic retargeting on Google, there was a significant difference in the number of clicks (M = –19.324, SD = 20.911, t(107)

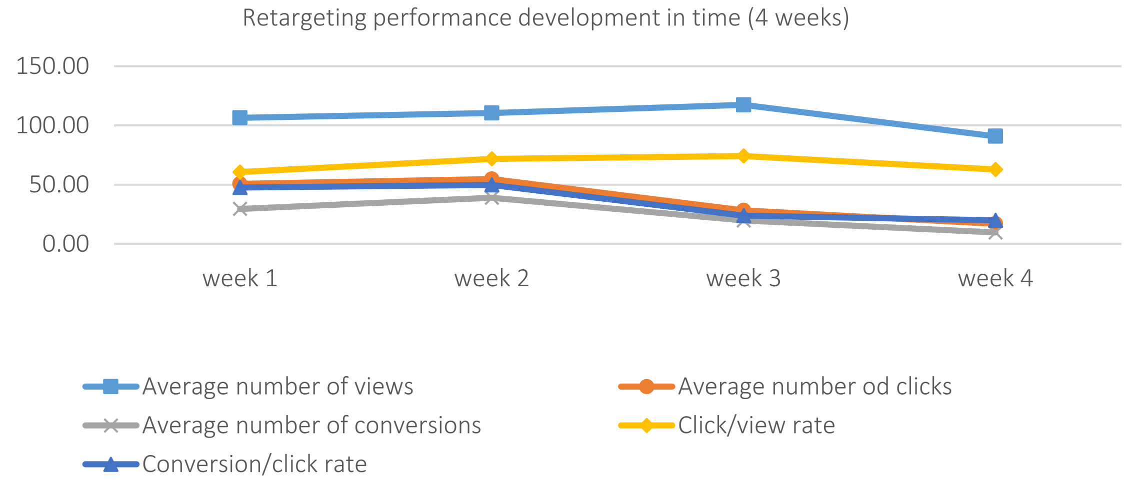

Figure 4. Retargeting performance development over time

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Table 5. Paired samples test: Standard and dynamic

	Performance metrics	Paired Differences					t	df	Sig. (2–tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
GOOGLE	Number of views	–4.352	76.184	7.331	–18.884	10.181	–.594	107	.554
	Number of clicks	–19.324	20.911	2.012	–23.313	–15.335	–9.604	107	.000
	Number of conversions	–22.231	5.902	.568	–23.357	–21.106	–39.145	107	.000
	Click/view rate	–.044	.042	.004	–.052	–.036	–10.891	107	.000
	Conversion/click rate	–.084	.101	.010	–.103	–.064	–8.587	107	.000
META	Number of views	56.120	69.741	6.711	42.817	69.424	8.363	107	.000
	Number of clicks	25.593	17.529	1.687	22.249	28.936	15.173	107	.000
	Number of conversions	–4.963	13.157	1.266	–7.473	–2.453	–3.920	107	.000
	Click/view rate	–.000	.076	.007	–.014	.014	–.049	107	.961
	Conversion/click rate	–.134	.111	.011	–.155	–.113	–12.691	107	.000

= –0.594, p = 0.000), in the number of conversions (M = –22.231, SD = 5.902, t(107) = –39.145, p = 0.000), and in the click/view (M = –0.044, SD = 0.042, t(107) = –10.891, p = 0.000) and conversion click rates (M = –0.084, SD = 0.101, t(107) = –8.587, p = 0.000). While there was a difference in the number of views, it was not statistically significant (p = 0.554). Regarding retargeting in Meta Ads, significant differences were found for the number of views (M = 56.120, SD = 69.741, t(107) = 8.363, p = 0.000), number of clicks (M = 25.593, SD = 17.529, t(107) = 15.173, p = 0.000), number of conversions (M = –4.963, SD = 13.157, t(107) = –3.920, p = 0.000), and conversion/click rate (M = –0.134, SD = 0.111, t(107) = –12.691, p = 0.000). However, the differences in click/view rate were not statistically significant (p = 0.961).

Finally, the last research hypothesis (H3) examines the impact of cookie legislation changes from opt-out to the opt-in regime, which took place in the Czech Republic in January 2022. Tables 6 and 7 present the results of paired T-tests for Meta Ads and Google Ads, respectively, comparing values for advertising campaigns from 2021 to 2022. For both advertising platforms, Meta Ads (standard: M = –134.241, SD = 60.599, dynamic: M = –100.556, SD = 62.227) and Google Ads (standard: M = –140.241, SD = 59.866, dynamic: M = –165.861, SD = 58.422), the paper observes a significant decrease in the recorded number of clicks leading to a website visit regardless of the type of audience or type of retargeting. Similarly, the results indicate smaller conversions (Meta standard: M = –19.667, SD = 28.450, dynamic: M = –128.444, SD = 66.172, Google standard: M = –42.926, SD = 43.951, dynamic: M = –139.750, SD = 69.890). In addition, the study can record a decrease in the number of views measured as the number of ad impressions, 67.123.

Despite the changes in the cookie tracking, the click/view and conversion/click rates for standard retargeting are not as heavily affected as other metrics. Therefore, standard retargeting maintains its effectiveness. On the other hand, dynamic retargeting in advertisements with personalized product listings suffered more significantly from the restrictions. For both advertising platforms, the collected data suggested slight effectiveness improvement for the standard retargeting in terms of click/view and conversion/click rates even after the cookie regime change in January 2022 (Meta standard: M = 0.074, SD = 0.087; M = 0.276, SD = 0.097; Google standard: M = 0.001, SD = 0.072; M = 0.197, SD = 0.135; respectively). The negative effects for dynamic retargeting consisted in the negative paired T-test values for the click/view and conversion/click rates (Meta dynamic: M = –0.057, SD = 0.057, M = –0.241, SD = 0.150; Google dynamic: M = –0.140, SD = 0.067; M = –0.134, SD = 0.182; respectively).

In conclusion, all the three hypotheses were confirmed. The results show that effectiveness of retargeting changes over time (Hypothesis 1) and that after two weeks the average number of clicks, average number of conversions, and conversion/click rate starts to decrease while the average number of views and the click/view rate peek during the third week. In addition, the study recorded differences in performance between standard and

Table 6. Paired samples test: Meta 2021 and 2022

Performance metrics		Paired Differences							
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference		t	df	Sig. (2–tailed)
					Lower	Upper			
STANDARD	Number of views	–510.944	93.267	8.975	–528.736	–493.153	–56.932	107	.000
	Number of clicks	–134.241	60.599	5.831	–145.800	–122.681	–23.021	107	.000
	Number of conversions	–19.667	28.450	2.738	–25.094	–14.240	–7.184	107	.000
	Click/view rate	.074	.087	.0081	.057	.091	8.827	107	.000
	Conversion/click rate	.276	.097	.009	.257	.294	29.507	107	.000
DYNAMIC	Number of views	–160.713	68.146	6.557	–173.712	–147.714	–24.509	107	.000
	Number of clicks	–100.556	62.227	5.988	–112.426	–88.685	–16.793	107	.000
	Number of conversions	–128.444	66.172	6.367	–141.067	–115.822	–20.172	107	.000
	Click/view rate	–.057	.057	.005	–.068	–.047	–10.478	107	.000
	Conversion/click rate	–.241	.150	.014	–.270	–.213	–16.709	107	.000

Table 7. Paired samples test: Google 2021 and 2022

Performance metrics		Paired Differences							
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference		t	df	Sig. (2–tailed)
					Lower	Upper			
STANDARD	Number of views	–421.537	118.582	11.411	–444.157	–398.917	–36.943	107	.000
	Number of clicks	–140.241	59.866	5.761	–151.660	–128.821	–24.345	107	.000
	Number of conversions	–42.926	43.951	4.229	–51.310	–34.542	–10.150	107	.000
	Click/view rate	.001	.072	.007	–.004	.024	1.443	107	.152
	Conversion/click rate	.197	.135	.013	.171	.223	15.159	107	.000
DYNAMIC	Number of views	–238.778	67.123	6.459	–251.582	–225.974	–36.969	107	.000
	Number of clicks	–165.861	58.422	5.622	–177.005	–154.717	–29.504	107	.000
	Number of conversions	–139.750	69.890	6.725	–153.082	–126.418	–20.780	107	.000
	Click/view rate	–.140	.067	.006	–.153	–.127	–21.599	107	.000
	Conversion/click rate	–.134	.182	.0178	–.168	–.099	–7.613	107	.000

dynamic retargeting (Hypothesis 2). These differences appear to be contextual and dependent on the advertising platform and its ability to personalize content based on the information about the users and the ability to adapt the content to the user's browsing needs. Finally, Hypothesis 3 seems to be valid especially for the dynamic retargeting that was affected by the cookie tracking regime changes most noticeably in terms of the click/view and conversion/click rates. This outcome of the experiment suggest that while online retargeting remains an effective tool, the level of ad personalization may suffer from the lack of data previously collected by the cookie trackers.

5. DISCUSSION

The findings suggest that the performance of the retargeting ads slightly differs across the two platforms (Google and Meta). This difference may be caused by the browsing context in which users come across the ads. Regarding Google, ads are usually displayed as a response to a keyword search, while on Facebook and Instagram, ads are instead connected with interests and previous behavioral patterns. Therefore, users coming across Google ads usually browse the Internet with a purpose (utilitarian browsing), while users going through social networks do it for entertainment purposes (hedonic browsing) (Indrawati et al., 2022).

The browsing context determines the follow-up behavior. When users with utilitarian motives see an ad that satisfies their search query, they respond to it. As a result, they tend to follow a direct shopping path while being less likely to buy other products (Indrawati et al., 2022) impulsively.

On the other hand, Facebook and Instagram users do not browse the social networks intending to

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shop. However, when they see an ad with a product they previously browsed, they may be convinced to impulse buying. Therefore, the hedonic motivation also produces more clicks on other products, which explains the higher number of conversions in the case of Meta Ads (Tuna et al., 2016). This difference may be the outcome of the different tracking techniques these two advertising platforms apply. Since social networks have more opportunities to analyze the behavioral patterns of their users' interests and para-social relationships (Semerádová & Weinlich, 2019), their targeting parameters are much more specific and allow for more robust targeting. At the same time, Google cannot target the ads based on para-social relationships since the company tracks the users using keyword search and web-based actions (Google, n.d.b; Vecchione et al., 2016), and thus Google retargeting is more suitable for utilitarian targeting.

Finally, the study examined the performance of retargeting ads over time. The performance was growing at first and after peeking during the second week started decreasing. The initial gradual growth can be explained by the ad learning stage, during which the algorithms test which ad configuration will work best. The learning stage is used by both Meta and Google Ads (Meta, n.d.d; Google, n.d.f; Choi & Sayedi, 2019). On the other hand, the decreasing trend will likely be influenced by the size of the retargeting audience. Retargeting audiences consist of users who previously interacted with the brand and depended on other activities and ads. Therefore, the retargeting audiences were relatively smaller since the analysis targeted only one product category due to the budget restrictions given by the online store owner.

The data for this study were collected with the help of a Czech online store in real-life conditions. The authenticity of data collected outside artificial experimental settings contributes to the existing body of knowledge by providing new findings of the differences in the same automated advertising tools provided by two advertising platforms and by shedding some light on the role of user data in the targeting processes applied by Meta and Google. Despite the authenticity, this study also has some limitations. Programmatic advertising and all online activities a brand carries out create one interconnected ecosystem. While automatic retargeting represents a powerful tool, its effectiveness depends on the quality of retargeting lists created via other types of advertisements and other brand activities. This analysis could not isolate and influence all these online efforts of the Czech store, and therefore this experiment was run under the assumption of ceteris paribus.

CONCLUSION

This study analyzed the retargeting effectiveness in terms of type (standard, dynamic), advertising platform (Meta Ads, Google Ads), and ad performance development over time. Overall, the results confirm that retargeting Meta and Google ads represent a powerful example of marketing automation that can help brands and companies harness the power of content personalization.

However, to use this type of advertising correctly, the advertisers must understand how standard and dynamic retargeting works and what data Meta Ads and Google Ads use to configure the retargeting campaigns. Furthermore, in terms of conversion/click rate, while Google ads are more suitable for standard retargeting and utilitarian contexts ($M = -0.084$, $SD = 0.101$, $t(107) = -8.587$, $p = 0.000$), Meta ads work best with dynamic retargeting that can come through hedonic browsing on social networks ($M = -0.134$, $SD = 0.111$, $t(107) = -12.691$, $p = 0.000$).

In addition, the advertisers may also reconsider the goals they want to achieve with retargeting ads. Nevertheless, the results of this study imply that retargeting ads work differently in different decision-making stages. For example, Google retargeting performed better in converting users into customers, while Meta retargeting generated more visits and conversions without necessarily leading to immediate purchases. Retargeting ads can, thus, be used also in the middle stage of the TOFU-MOFU-BOFU advertising funnel to enhance the consideration phase.

This paper also addressed the raising concerns about the changes in cookie-based tracking. Thanks to the current legislation change in the Czech Republic, this experiment was run both in the opt-out and opt-in regimes. While there are differences in the total numbers of tracked users, these do not affect the performance of programmatic advertising that severely. Dynamic retargeting showed the strongest negative effects for the click/view and conversion/click rates (Meta dynamic: $M = -0.057$, $SD = 0.057$, $M = -0.241$, $SD = 0.150$; Google dynamic: $M = -0.140$, $SD = 0.067$; $M = -0.134$, $SD = 0.182$; respectively), however it still brought positive outcomes in the form of converted users.

The only problematic step is thus receiving the user's consent with cookies. Programmatic advertising and especially automatic retargeting still represent the best options for online marketing interactions with potential customers. While there is no doubt that programmatic advertising is conditioned by the quality and availability of user data, it is crucial to distinguish in which part of the advertising process the user data are applied. The fact that a number of ad impressions (views) lead to a certain number of website visits and conversions recorded by website analytics does not mean that the advertising effectiveness may be measured only by these numbers since the numbers might be even higher; also, cookie consent rejections left unregistered by the tracking and analytical systems.

AUTHOR CONTRIBUTIONS

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