Dynamic Retargeting
-The Holy Grail of Marketing?

Master's Thesis 30credits
Department of Business Studies
Uppsala University
Spring Semester of 2017

Date of Submission: 2017-05-30

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Abstract

To reach consumers with marketing in today's digital climate is in need of highly accurate and relevant ads. Consumer are in constant information bombardment and increasingly tougher competition is making it more complicated to reach your target consumers that wants to see and get what they want whenever they want it. Dynamic retargeting is highly intelligent, utilizing the latest technology for performance marketing, which enables ads that are highly accurate and relevant through personalization, cost efficient and revenue generating. This is possible due to algorithms targeting most likely conversion (company defined valuable post ad click actions) targets and at the right moment in their purchasing funnel.

Our findings, based on analysis of dynamic retargeting campaigns from a Swedish-, Danish- and Finnish company, support previous literature that ad personalization and timing will affect consumer engagement and also their purchase behavior, positively affecting ROI. The data show that dynamic retargeting considering timing (in this case, ads targeted directly after browsing instead of 8-hour delay) had 3.4% higher banner click-through rate and a conversion rate that was 13.1% higher. We also found that dynamic retargeting is increasing ROI. The result show that dynamic retargeting had a incremental ROI of 62 times the investment compared to buyers not targeted with dynamic retargeting. Lastly, we recognized the importance of being able to recognize users across different devices. We found that 72% of buyers used at least 2 devices and switched at least 3 times before the purchase, which highly suggest cross device recognition as an important feature in dynamic retargeting, in order to gain efficiency in ad delivery, costs and results.

Key words: *retargeting, dynamic retargeting, personalization, recommendation algorithm, bidding algorithm, behavioral algorithm, machine learning, big data, banner, ads, click through rate, conversion, return on investment.*

1. Introduction

The technology of today has revolutionized the way advertising can be done. It has enabled companies to be precise in how and to whom they target their communications, to the opposite of traditional "spray and pray" advertising through channels such as newspapers and broadcast television. However, digitalization is not only enabling new ways to perform advertising, it is also changing the behaviors of the target audience - the digital consumer. In 2016 around 80% of Swedish consumers was using Internet everyday and 60% did online purchases (SCB, 2016). The same year in America ⅔ shoppers did online browsing once or more every month (Criteo, 2016a). Digital consumers are also more independent in the way they shop, as result of technological inventions helping consumers both in the gathering pre-purchase information (e.g. with a smartphone or tablet), but also by being platforms from which purchases can be done. The digital consumers want to self-service by helping themselves when they feel like it (Russell, 2013; Court, Elzinga, Mulder and Vetvik, 2009) and they are multichannel and are thus browsing and buying amongst different channels (Tonkin, Whitmore and Cutroni, 2011; Court et. al., 2009).

Multiple touch points from different marketing channels are often preceding the actual purchase. In the digital environment the consumer-purchasing funnel might involve touch points from channels such as paid search (e.g. Google search), display ads (banners) and email. This makes it important to understand the complex customer journey across marketing channels, in order to increase advertising efficiency such as channel cost allocation based on the level of different channel interactions among consumers (Li & Kannan, 2014). Additionally, technological development have increased consumer multitasking with different devices, which lowers the attention towards each task and thus complicates companies abilities to get the attention of consumers to their ad promotions. (Russell, 2013; Fuchs, Prandelli and Schreier, 2010; Teixeira, 2014). One example is consumers watching TV and shift attention back and forth between their smartphone and TV. To highlight this phenomenon, the average amount of TV ads considered viewed with relevant attention have dropped from 97% in the beginning of 1990s to under 20% in 2014 (Teixeira, 2014). Furthermore, today consumers are getting bombarded with ads from different channels in different devices, which can easily be overwhelming, causing them to turn of attention towards ads (ibid.). These impatient and ad overexposed consumers is a problem for advertisers and require new ways to trigger consumer attentions and interactions.

In the marketing wilderness with self realignment customers and saturation of both time and marketing, the marketers need to adapt to the new environment, from mass advertising to individual-level personalization (Norman, 1999). This research investigates the relatively new phenomenon dynamic retargeting, which is intelligent, highly personalized and behavioral targeted ads that possibly match the current digital marketing environment. The phenomenon includes multiple algorithms: recommendation-, bidding- and behavioral algorithms. The algorithms are interconnected with each other and are enhanced with machine learning and big data, which could create more effective retargeting ads. We refer to this phenomena as: *Dynamic Retargeting* (Criteo, 2016b; Google, 2017a),which is different to a retargeting ad that retarget customers visiting a webpage with a traditional generic ad that are fixed in its design and content (Lambrecht and Tucker, 2013). It is also different compared to a personalized retargeting ad that do not have machine learning capabilities, but retarget customers with an ad that (only) change the visualized message dependent on customer data generated from what product/service the customer browsed for. Thus, using a simpler version of recommendation algorithm (Bleier and Eisenbeiss, 2015a).A summary of the different retargeting concepts is presented in the end of the introduction chapter in table 1.3.1.

Consequently dynamic retargeting is a further evolution of personalized retargeting by incorporating machine learning algorithms in the ad distribution and therefore create a new concept which should be treated separately to avoid confusing mixes.

1.1 Digital advertising

Digital advertising gives companies the opportunity to take advantage of "Big Data", a concept that includes the utilization of large quantities of data by smart algorithms. Companies can collect information about their site visitors via internal server based log files and/or page tags using cookies, in order to understand consumer behaviors (Clifton, 2010). This behavior data gives marketers information on an individual level and enables advertising based on what the customer's actually do and what they actually want (Lee and Dempster, 2015; Tonkin et al, 2011).

The Big Data concept has also enabled cost efficiencies in digital advertising. The ability to measure the volume of target audiences and their interaction with marketing campaigns enables billing schemes where companies only pay for measurable results. This is called performance marketing, where the performance, e.g. amount of clicks or impressions (ad visualizations) of a certain ad is leading to a cost. If the performance of the ad is getting better, the cost goes up. A summary of performance marketing terms is presented in the end of the introduction chapter in table 1.3.2.

In order to improve advertising performance, today's ad platforms (e.g. Facebook, and Google) allows advertisers to target marketing communication toward specific consumers based on factors such as geographies, demographics, behaviors and interests which increase the accuracy of marketing activities and make it possible to create more specific messages to more specific target group. This improves marketer's ability to erase "blind marketing" toward non-interested audiences and increase effect among relevant audiences. Nevertheless, in a world where consumers gets bombarded by marketing messages from all sorts of actors, both online and offline, consumers ability to realize marketing offerings decrease.

The retail industry constantly intensifies its online advertising efforts, from 775 million in 2008 to $2.60 billion in 2014 (Miller and Washington, 2013) and standard display banners are increasingly struggle to gain consumers attention (Cho and Cheon 2004). It is not helping that humans have gotten a shorter, on average, attention span than a goldfish, 8 seconds compared to a goldfish 9 seconds, which is seemingly due to our digital usage that have an increased negative effect on marketing efforts (Microsoft, 2015). As a result, the overall worldwide ad banner click-through rates (CTR, clicks/impressions) have in 2017 come down to 0,17% (smartinsights, 2017) compared to 2% in 1995 (Cho and Cheon 2004).

1.2 Retargeting

Retargeting is becoming the norm with companies as eBay, Amazon, Facebook and Google offering different solutions (Peterson, 2013; Sengupta, 2013). Practitioners are raising their budget for retargeting (Hamman and Plomion, 2013; WARK, 2015), and more specifically showed one survey consisting of 250 European practitioners that ⅔ of the marketers planned to increase their budget for retargeting, indicating that retargeting meet their expectations (WARK, 2015). On the contrary, many marketers have major concerns for retargeting in regard to inaccurate ad messaging (Handley and Lucy, 2016) and that customers are likely to multichannel and use multi-device creating issues regarding consumers that may be unrecognizable due to multi-cookies between devices (Handley and Lucy, 2016; Nottorf, 2014). Previous investigation regarding retargeting has shown that high frequency, for retargeting, can result in persuasion knowledge and that retargeting may also affect brand attitudes negatively (Kjærbøll, 2015). Retargeting can quickly lose effectiveness over time and is only efficient if it is relevant, which is measured by browsing behavior (Bleier and Eisenbeiss, 2015a). This create a need to further improve the effectiveness of retargeting to create reliable ads that practitioner can trust. In order to achieve greater effectiveness, many marketers have taken to dynamic retargeting that, as mentioned, change ad design and ad timing on ad motive congruent website (Criteo, 2016b; Google, 2017a).

90% of companies want to do more consumer personalization but less than 20% are doing it (Handley and Lucy, 2016). Maybe this is due to mixed result amongst previous research regarding retargeting and uncertainties of the subject in general. Lambrecht and Tucker (2013) found that personalized retargeting ads are on average less efficient than generic ones and is only efficient if the customer have evolved product preferences, and thus timing is very important. In comparison Bleier and Eisenbeiss (2015a) showed in their study that personalized retargeting is efficient if the customer are in the beginning of the purchase stage, and thus do not have evolved preferences. However, the mixed result seemingly is due to differences in researched industry, respectively tourism and fashion. Retargeting thus need to be intelligent in terms of targeting based on company industry, developed interests and consumer contexts, in order to efficiently reach out to potential customers. In 2016 impulse purchases accounted for one third of online purchases in America (Criteo, 2016a), which also highly suggests that intelligent recommendations from dynamic retargeting is important for advertising strategy. Since the consumer are becoming more and more demanding and want the right message at the right time, dynamic retargeting could increase the probability to trigger consumer purchase behavior (Court, et al 2009).

1.3 Problem Formulation

We found a lack in previous research regarding dynamic retargeting. Previous literature by Lambrecht and Tucker (2013) state to investigate dynamic retargeting. Nevertheless, from this study's point of view, a retargeting ad that are only personalized based on what product(s) the user previously have clicked on, with no ad recommendation consideration based on behavioral algorithm, or constantly improved by machine learning capabilities, is referred to as a personalized retargeting ad. Bleier and Eisenbeiss (2015a) studied how the level of personalization affect personalized retargeting ads efficiency compared to generic retargeting ads. Summers, Smith and Reczek (2016) study how customers becomes affected by behavioral targeted ads, ads that target users based on browsing behavior. Thus, some of the factors included in dynamic retargeting have been researched, but not the efficiency of the complete phenomena. We believe that retargeting strategy will be successful if it adapts to the consumers at an individual level. In order to find hypothesis that explains how ad adaptation can make retargeting more efficient, we will go further into previous research of consumer behavior, ad efficiency and retargeting in general. We expect that by implementing a dynamic retargeting engine, issues regarding consumer multi-channel behavior, cross-device usage and inaccurate ad communications may be solved. Furthermore, an intelligent recommendation system may also enhance consumer engagement and purchases, which would increase ad efficiencies. Therefore, our research question is:

How does dynamic retargeting influence consumer ad engagement and purchasing behavior?

Table 1.3.1 - Summary of retargeting types

Retargeting type	Recommendation algorithm	Bidding algorithm	Behavioral algorithm	Machine learning
Generic retargeting	-	-	-	-
Personalized retargeting	X	-	-	-
Dynamic retargeting	X	X	X	X

Table 1.3.2 - Overview of performance marketing terms used in this paper

Performance marketing terms	Abbreviation	Explanation
Impressions	-	The amount of times the ad was visualized to the target audience.
Ad clicks	-	The amount of times the ad was clicked.
Click-through-rate	CTR	Ad clicks / amount of impressions. Highlights clickability of campaigns, advert-sets (target audience) or ads.
Cost-per-click	CPC	The cost per ad click. Target audience or content in the ad may be optimized if the CPC is considered too high.
Cost-per-mille	CPM	Cost per 1000 impressions. Often considered in branding campaigns where a broad reach at a low price is desirable.
Conversions	-	Valuable post ad-click actions decided by the advertiser. For instance, purchase, app-install or site registrations.
Conversion rate	CR	Conversions / ad clicks. Optimization may include more relevant target audience or a better post click conversion-landing page.
Real-time-bidding	RTB	RTB auction system enables a bidding system that is automatized through programmatic networks. Each advertiser set up their bids on what an impression is worth on a specific network, the highest bidder gets the ad impression.

2. Theoretical Framework & Hypotheses

In this chapter we will give an introduction to performance marketing and discuss previous research in ad retargeting and different aspects of it, which will lay ground to the formation of our hypotheses regarding dynamic retargeting.

2.1 Performance Marketing

In order to better motivate marketing activities marketers have for a long time searched after an ideal way to measure marketing performance, in order to determine accountability for financial results (Stewart and Gugel, 2016). In 2011 67% of CEOs state that marketing efforts was not measured and 20% of CEO's was not sure if marketing efforts made a difference at all(Marketo, 2011). Marketing activities can be, and have historically been, difficult to measure due to lack of meaningful metrics. Furthermore, long-term effects have also been hard to link to certain marketing efforts (Stewart and Gugel, 2016). This is something that constantly improves with increasingly advanced performance tracking tools, from which marketers can track marketing campaign results and consumer behavior over time. Research has shown that the ability to measure performances of marketing activities has a positive impact of the overall performance of the firm (O'Sullivan and Abela, 2007). One reason is because tracking of campaign performances gives knowledge about marketing activities that can be optimized. For instance, allocating resources towards top performing activities.

Performance marketing use big data analytics to plan and create marketing campaigns on search networks, websites/blogs, apps and social media (Tonkin et. al., 2011). From the data analytics, marketers becomes able to foresight ad performances and calculate overall marketing campaign results, even before the campaign is launched. This opens for smart and cost-efficient marketing strategies (Lee and Dempster, 2015; Tonkin et. al., 2011).

One way to measure digital advertising is with ad tracking tools, which can provide important information about which types of conversions certain ads lead to. Conversions are post ad-click actions that have been defined as valuable for a business, such as a purchase, ad-reply or phone-call (Google, 2017b). This gives advertisers knowledge about which customers thatis more or less valuable for further advertising. For example, advertisers can exclude purchasing customers from further same-ad-impressions, in order to avoid cost inefficient ads and negative attitudes from consumers who already purchased the product promoted by the ad (Pearson, 2015).

By being able to measure ad results, different types of online inventory in which ads can be visualized have become more or less demanded. Online inventory include, for instance, certain positions on web pages, search engines, apps or email, where ads can be seen. This have led to an auction based system called real time bidding (RTB), which means that advertisers bid on certain online inventory in which their ads may appear (Nottorf, 2014). It involves both display ads and search ads, where the highest bidder gets premium spots.

In the upcoming sections we will discuss different aspects within performance marketing. These have an important role in the development of retargeting ads and especially dynamic retargeting.Hypothesis will conclude the theoretical discussions and help us answering our research questions.

2.2 Multi Channel Advertising

In this section we describe the importance of being able to measure advertising impact from multiple channels and why the combination of different channels may lead to valuable advertising results. Multi channel advertising play an important role in dynamic retargeting, since it is desirable to track the consumer across multiple digital channels, in order to recognize which channel that generates the most beneficial ad results.

The importance to take the whole process of the customer purchasing process into account has long been debated (Bettman, 1979). In order to understand the total marketing performance from every marketing activity, advertiser must be able to track and understand the impact each marketing channel has to the overall marketing strategy (O'Sullivan and Abela, 2007). Performance marketing tools have enabled to gather data and track result from multiple digital marketing channels,as well as TV/radio, print ads and direct mail (Tonkin et. al., 2011). However, it is very important to evaluate the accuracy of the measured data, in order to get valid results from marketing analysis. Otherwise, marketing actions from such analysis would be inefficient and could lead the company in the wrong direction.

In terms of advertising, different channels may generate different levels of ad efficiencies. Dahlén (2005) have shown that ad efficiencies are dependent on the media context in which the ad impression takes place. By being creative in the choice of media, through which the ad is visualized and how the ad is communicated, different positive outcomes may occur. For instance, by finding a media which in itself functions as a part of the ad message, instead of having ads that are the sole communicator of the marketing message (e.g. traditional ads in newspapers). It could be native advertising, which are ads that are integrated in the content of a site or app to create a greater experience and improve consumer interactions. It may result in positive consumer associations such as higher ad credibility and brand/ad attitudes (Dahlén, 2005). Nevertheless, without reliable tools to measure these kind of outcomes, evaluation would only be subjective opinions about the marketing effort. Furthermore, if you cannot determine the value of the marketing outcome from a creative choice of media, the worth of the effort to launch these kind of campaign may not be worth it. The type of content that have to be produced in order to have a fit with the creative choice of media, can be time consuming and expensive in production costs.

Bronner and Neijens (2006) found that the perception of a site may be connected to the ads on that site. If ads are perceived as useful, consumers would also perceive the site to be useful. Therefore, creativity may lie both in the site, the media, but also in the formation of the ad. Additionally, consumer online ad interactions impact the amount of time consumers decides to spend on sites, where annoying and disturbing ads results in consumers leaving sites at an early stage without any consideration of engaging with the ad (Danaher et. al. 2006; Danaher 2007).Thus, the channels in which the ad takes place (Dahlén, 2005) and the ad itself (Danaher et. al. 2006; Danaher 2007) affect consumer perceptions and may thereby influence decisions among consumers.

Efficient multi channel advertising requires the advertiser to understand different processes in the consumer-purchasing funnel, from initial consideration over to active evaluation and purchase closure (Court, et. al. 2009). In these processes, consumers are crossing many channels back and forth, which results in multiple touch points (Tonkin et. al. 2011; Court, et al 2009). By analyzing different channel touch points and their effect on consumer purchasing behavior, performance marketing measurement tools can give information about how to best optimize ad deliveries through multiple channels. For instance, if a certain touch point behavior or type of media channel is recognized to more often bring valuable conversions, optimization by allocating advertising activity in certain channels may improve advertising performance. However, the combination of ads from different channels may be the recipe of success, where a specific order of ad and consumer interaction from different channels may be what triggers valuable consumer behavior. This is supported by Nottorf (2014) who found that repeated impressions of display banners declined ad clicking probability, but, if the consumer preceded the display banner impressions with a click on a search banner from the same company, this stabilized or increased the clicking probability. Thus, the combination of advertising channels may increase ad performances and, also, enhance long term advertising effects if, for instance, display advertising is preceded by search advertising (ibid.). This gives opportunities for retargeting ads, by retarget display ads to consumers who previously clicked on a search ad.

2.3 Consumer Purchasing Funnel

In this section we describe consumer purchasing funnel and why advertising must consider it in order to achieve desirable ad campaign results.

Today's advertising models are based on the traditional marketing funnel AIDA (Awareness, Interest, Desire and Action) (Vakratsas and Ambler, 1999). AIDA is very similar to the digital purchase funnel presented by Google: Awareness (See), Consideration (Think), Action (Do) and Advocacy (Care). In this model, traditional static banners is mainly a tool to build brand awareness, search (e.g. searching for a specific brand or product on Google) is placed under the consideration stage, retargeting ads under action and advocacy may involve activities such as post purchase follow up with email. Thus, retargeting fit the later stage when the customer is about to take action, such as a purchase of a specific product (Casablanca, 2016). Awareness and interest may occur at the same time, when interest is established customers enter a consideration-stage. In this stage they are evaluating already known brands, search for further information and compare benefits with different products. When evaluating, the customers also reduce number of options in order to find the desired product before they take action and make a purchase. (Van den Bulte and Lilien, 2003).

Court et. al., (2009) describe a circular decision-making purchase process (chart 2.2), which involves *Initial consideration*, *Active evaluation, Moment of purchase* and *Post Purchase.* Similar to the AIDA and the Google model, brands are included in the initial consideration stage based on consumer brand awareness and interest. However, it differs in regard to that additional brands may be added in the active evaluation stages. In the evaluation stage it is more difficult for companies to control the flow of product information to potential consumers. Consumers can easily share company information on social media and review company products on review sites, which have serious impact on the decision making processes of other consumers (Winer, 2009).

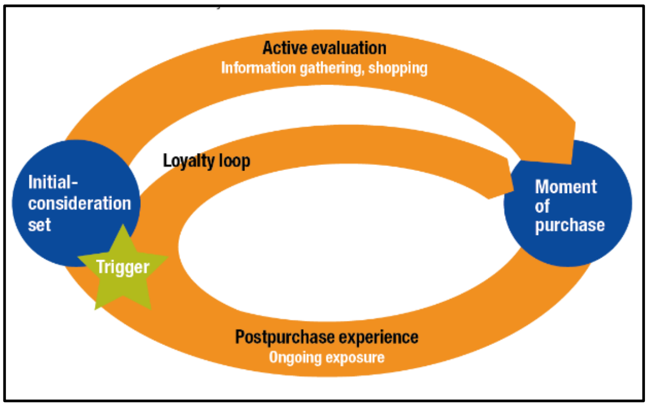

Chart 2.2 - Circular decision-making purchase process

In this stage two-thirds of touch points involve consumer-driven marketing activities, such as internet reviews and word of mouth (WOM), and, a third involve company-driven marketing (Court et. al., 2009). After the evaluation stage the moment of purchase hopefully occur and finally post purchase experience where activation (get consumers to use and experience the bought product) and reactivation of the consumers is the goal (ibid.). Once activated, reactivation activities, such as asking for feedback or discount offers may help to bring consumer back into the funnel and enter a new consideration stage. Therefore, the goal should not only be to get a purchase, instead, by establishing a caring relationship with the consumers through satisfactory post purchase experiences, rewarding loyalty may be the result. If the company accomplish successful relationship marketing and achieves loyal customers, the loyalty loop (visualized in chart 2.2) would lead to re-purchases without threats from competition in consideration and evaluation stages (Court et. al., 2009).

Retargeting cannot help firms entering the initial consideration stage, due to that retargeting is a post awareness activity (Casablanca, 2016). In the consideration stage the goal is to gather consumer awareness and interest behavior, from which retargeting may act on. Retargeting may also target sites with consumer-driven marketing activities, such as review-sites, blogs and WOM on social media. Imagine the customer visit a firm website, browsing products and by that leaving a data trail for companies to pick up. Later the consumer continues the evaluating process on sites or apps with consumer driven marketing activities. This will increase the likelihood of reaching consumers in those places with retargeting, if the sites/apps are included in an ad network that allows retargeting. This may help the firm to better control consumer-driven messages online, due to a ad presence and thus an opportunity to influence customers, in the evaluation stage, on sites otherwise controlled by consumer driven messages.

The complex purchasing funnel of the digital consumer makes it important for companies to find ways to show relevant and timely accurate ads to their consumers, in order to increase probabilities of successful advertising. Both ad timing, reaching consumers at the right time in their purchasing process, and place, the media channel in which the ad impression takes place, is affecting the probability of getting valuable conversions, like purchases, from the consumers.

2.4 Ad Personalization & Consumer Behavior

In this section we describe how ad personalization, one of the feature in dynamic retargeting, affects consumer behavior. We both explain how ad personalization triggers rewarding consumer behaviors (e.g. improved CTR from higher ad relevancy) and how it may result in negative consumer behaviors such as feelings of intrusiveness and provocation.

Ad Timing and type of marketing channel is not the only aspect of successful advertising. The key for successful digital marketing campaigns is to understand the digital consumer and their needs as well as serving them with personalized valuable content and/or offerings (Tonkin et. al., 2011). Previous research has concluded that greater specificity between the marketing message and target group leads to increased relevance and thus higher consumer response (Dias et. al., 2008).

The experience consumers have with online content is what later defines their level of engagement toward the content sender (e.g. a brand or website), which in turn may affect ad effectiveness. Content in online settings may engage consumers in utilitarian or/and intrinsically enjoyable ways (Calder et. al. 2009). Utilitarian content would help the consumer in terms of important decision making and life accomplishments, while intrinsically enjoyable content would simply be something enjoyable for the consumer that may help them to get away from everyday pressures (ibid.). Calder et. al. (2009) found in their study a positive relationship between online engagement and ad effectiveness.

Content is also important when creating digital ads. Increasing ad relevancy through personalized offerings is likely to increase consumer engagement due to previous experiences with such content. Bleier and Eisenbeiss, (2015a) found that personalized ads have higher CTR compared to non personalized ads in all of the stages in the purchasing funnel, and that all ads disregarded to degree of personalization was most effective in the information stage. The evaluation-stage in the purchasing funnel was divided up into a information-, a consideration- and a post-purchase stage. Consumers stabilize their preferences during their gathering of pre purchase information and are therefore less dependent in the end of the decision process to company advice (Bleier and Eisenbeiss, 2015a; Simonson 2005; Hoeffler and Ariely 1999). Therefore, ad personalization through retargeting may enhance utilitarian and/or intrinsically feelings and improve ad efficiencies such as CTR, since the content in the ad would be based on previous consumer engagement with certain online content. This is also acknowledged with more recent studies supporting the idea that display ads need to be more visible, memorable, targeted and user traced, in order to enable ad optimization and increase ad efficiencies (Braun and Moe, 2013; Lambrecht and Tucker, 2013; Schumann, Wangenheim, and Groene, 2014; Urban, Liberali, Macdonald, Bordley and Hauser, 2014; Bleier & Eisenbeiss, 2015a).

However, there are not only positive outcomes from personalizing ads. Ad personalization may also provoke consumers. When ads are getting dangerously close to consumer interests and preferences, consumers may feel personal intrusion and that companies behave inappropriate. The consumer may feel like he or she is being followed and that their privacy is not respected. (King and Jessen 2010; White, Zahay, Thorbjornsen and Shavitt, 2008). Personalized ads may also lead to consumer irritations since the ads are more enforced. For example, showing a specific product that the target consumer has just been browsing may increase attention but can be referred to as more annoying (Cho and Cheon, 2004; Grant, 2005). This may lead to consumers not wanting companies to adjust ads, like with retargeting, according to their online behaviors (Guild, 2013). However, Bleier & Eisenbeiss (2015b) showed that trusted brands received 27% better CTR with retargeting (CTR increased from .40% to .51%) compared to less trusted brands where the CTR decreased with 46% (from .37% to .20%). Nevertheless, if retargeting is based on active and recurring consumption behaviors on company homepage or app, it can be assumed that some level of trust is already established among consumers.

2.5 Retargeting & Ad Impression Timing

In this section we describe the impact ad impressions timing has in retargeting. We discuss how it has on ad and how it improves ad efficiencies CTR and conversion rates.

Research has previously studied the long-term and short-term effect of marketing to improve accuracy when measuring the cumulative impact of marketing activities. Radio has longer lagged marketing effects than billboards (Berkowitz, Allaway and D'Souza, 2001a) and billboards have longer effects than newspapers (Berkowitz, Allaway and D’Souza, 2001b). In comparison, between the three medias, radio ads are entirely auditory while billboards and newspaper are visual. Radio and billboards are both mass-marketing with limited targeting possibilities, while newspaper ads can be placed in specific targeting sections. Therefore, digital display marketing that is highly targeted against a specific audience and with a purpose of helping the consumer to find a product in the end of the purchasing funnel, seemingly should have a short-term effect and only be useful when it is helpful for the customer. We found support for this reasoning with Breuer, Brette and Engelen (2011) who found that e-mails have a longer lagged effects than banners and that banners have a longer lagged effects than price comparison advertising (PCA). PCA is a specific type of affiliates marketing sites where the consumer can make price comparisons between products. Firms can also improve their ranking position by paying a premium and get their product to be recommended to consumers. In the study by Breuer, Brette and Engelen (2011) the PCA only gave result within the same day (19 hours after impression) but had the highest conversion rate, while banners gave result under 2.2 days and had a 129% lower conversion rate (ibid.).

Dynamic retargeting is a banner ad that, like PCA, recommend a product that the customer are interested in (Quantcast, 2016) and thus should have a higher conversion rate and have a short-term result, due to ads being targeted in the end of the purchasing funnel. However, dynamic retargeting ads are much more personalized and the ad is also shown on more congruent web sites. This should lead to even a shorter short-term result and higher conversion rates. Since the purpose of dynamic retargeting is to target user in end of their purchasing as a final push to get users to buy products they showed interests in, the purpose of the ad is fulfilled once the conversion is done. This support the short-term effect of dynamic retargeting and motivates the importance of ad impression timing.

Breuer et. al. (2011) found that advertising focusing on helping customers in the evaluation stage are more effective when targeted close to product browsing on a company website. The results from this study also showed that ad CTR performance ended within one day (ibid.). Similar results are gained by Bleier and Eisenbeiss (2015a) who estimated ad CTR development over time for personalized retargeting ads. They also found that personalized ads had higher CTR immediately after the user visited the online store and decreased over time, but was always more effective compared to non-personalized ads. Dynamic retargeting ads should therefore have a higher CTR if targeted immediately after browsing products on a online store compared to delaying the retargeting. As a result, this should lead to more conversions because of the increased amount of potential customers, who are in the end of their purchasing funnel, clicking on the ad. However, different types of product categories may involve different levels of sensitivity in terms of privacy, which may provoke consumers if they are directly targeted after browsing products they want to keep private. Furthermore, expensive products may also be something that consumers want to consider for a while without being pushed right after browsing products by retargeting to make the purchase. Therefore, ad impression timing should consider the type of product that the consumer have browsed, in order to avoid negative effects like feelings of intrusion.

Previous research in retargeting point to a very specific setting and a specific target group that want to be helped with the right message at the right time. If the consumer does not demand help, retargeting may only create concerns regarding privacy issues (Bleier and Eisenbeiss, 2015b; Lambrecht and Tucker, 2013). Therefore, if dynamic retargeting takes timing in the consumer purchase decision process into consideration, dynamic retargeting is likely to be successful. Therefore we propose the following:

Hypothesis 1: Ad impressions timing improves the CTR of dynamic retargeting

Hypothesis 2: Ad impressions timing increase consumer conversions of dynamic retargeting

2.6 Ad Recommendation Algorithms & Consumer Behavior

In this sections we describe the development of recommendation algorithms, which is an important feature of dynamic retargeting. We also describe the role ad recommendations have to advertising and how it can promote increased sales.

Large-scale e-commerce, as eBay and Amazon, use recommendation algorithms to help the customer in purchase decision making and by that increase sales (Li, Xhang and Wang, 2013). The gathering of consumer behavioral information from cookie-based browsing data and server-log files data have enabled marketers to offer specific and more personalized messages than ever before (Trusov, Ma and Jamal, 2016). From the data, recommendation algorithms can create performance marketing that offers product recommendations to consumers when they are browsing on, or return to, the company's website (Lambrecht and Tucker, 2013). Once a consumer have established a consideration set of brands on a web site and entered the evaluation stage in the purchasing funnel, companies may perform "just-in-time marketing" with recommendation ads on the website (Tonkin, et al, 2011).

The first recommendation algorithms were based on consumer purchase behavior statistics from which predictive modeling generated recommendations (Billsus, and Pazzani, 1998). In recent times machine learning have been applied to recommendation algorithms, because recommendations thereby becomes continuously more effective and accurate. Effectiveness for recommendation algorithms is often measured by mean absolute error, the average absolute difference between predicted action and actual action, and consequently how relevant the recommendation is for the user (Thorat, Goudar and Barve, 2015; Melville and Sindhwani, 2010).

There are three main categories of models for recommendation algorithms: content-based filtering, collaborative filtering and a hybrid of the two (Melville and Sindhwani, 2010). Content-based filtering utilizes characteristics of a product in order to recommend additional similar items. Thus, it requires developed user profiles that are based on consumer product preferences and also predefined features and values that describe each product as a vector of features (Manjula and Chilambuchelvan, 2016; Bossenbroek and Gringhuis, 2014; Melville and Sindhwani, 2010). Content-based filtering is therefore very dependent on accurate product values and feature descriptions, in order to be able to make accurate recommendations. Otherwise, consumers may be irritated due to recommendations that they would never consider to buy.

Collaborative filtering, like k-nearest neighbors algorithm, recommend a product based on what other users with similar behavior liked or purchased, by measuring the degree of closeness. Collaborative filtering compares a consumer's past purchases or stated preferences to the purchases or stated preferences of similar consumers from an existing database. This type of recommendation algorithm thus need often large data-set of data from other users together with the customer using the website to create a recommendation. (Bossenbroek and Gringhuis, 2014; Chiluka, Andrade and Pouwelse, 2011; Melville and Sindhwani, 2010). However, collaborative filtering that are model-based, meaning it use a part of a dataset to create a model that can make a prediction on a not complete dataset, gives a more accurate result compared to content-based filtering, it also help to boost both speed and scalability (Thorat, Goudar and Barve, 2015).

Efforts are also made to combine content-based filtering and collaborative filtering to create more effective recommendations, which previous research suggest to be true in some cases (Thorat, Goudar and Barve, 2015; Melville and Sindhwani, 2010; Campos, Fernández, Juan, and Rueda-Morales, 2010). A hybrid can be created in many different ways and both content-based filtering and collaborative filtering have their weaknesses and strengths that can be minimized and/or enhanced. The two methods can be used individually with a combined predictions, or integrate some characteristics of one model into the other model, or integrating both models characteristics into a new model (Thorat, Goudar and Barve, 2015).

Linden, Smith, and York (2003) claims that recommendation algorithms are a more effective form of targeted marketing, since it gives the customer a "personalized shopping experience".Dias et al (2008) showed a result of 0,5% increase of direct revenue for e-shop that started to use a recommendation algorithm. Adding behavioral characteristics to the recommendation algorithm can significantly enhance the effectiveness of the recommendation. Therefore can dynamic retargeting, that use behavioral algorithms to decide the recommendations, be more effective (Corbellini, Godoy and Schiaffino, 2016; Manjula, and Chilambuchelvan, 2016; Hu and Pu, 2011; Hu and Pu, 2010; Tkalcic, Kunaver, Tasic and Košir, 2009).

It is common that retargeting ads show a specific product that the consumer previously browsed before leaving the company website, which makes the ad more specific and targeted (Lambrecht and Tucker, 2013). This is created by content-based factors that are gathered from the user, as for example session-time for products watched and adding a product in the shopping cart or wish list (Godoy and Schiaffino, 2016) Thus, it do not use the algorithms described above. Dynamic retargeting use machine learning recommendation algorithms that, based on previous research above, should be more efficient (REFF). Therefore, in order to serve potentially valuable customers with personalized recommendations across the web, dynamic retargeting might be the solution. Recommendation algorithms may also, in regard to increased revenue, help to increase ROI.

2.7 Dynamic Retargeting & Intelligent Algorithms

In this final section we describe the dynamic retargeting data engine and what type of algorithms it is built upon. We will also in the end of this section present a model based on our hypotheses, which visualize how dynamic retargeting influence consumer ad engagement and purchasing behavior.

Dynamic retargeting use recommendation algorithm together with bidding- and behavioral algorithm, which enables a personalized ad recommendations on a individual level for every ad impression (Google, 2017a; Google2, 2016; Quantcast, 2016; Criteo, 2016b; Summers et. al. 2016). This is partly created through a behavioral algorithm that make an individual user profile, which reflects the type of behavior the customer have and sends out ads according to that behavior (Summers et al, 2016). It could be online behaviors such as clicking/viewing patterns, user interests and transaction histories. Google state that their algorithm calculates based on roughly fifty signals, including location, device, browser, referrer, session duration and page depth (Google2, 2016). Adroll also state to use an algorithm for customer behavior focusing on intent signals, as for example a customer comparing products, to predict buying intent similar to previous customers (Adroll, 2016; Adroll, 2015). This is referred to as predictive modeling, a behavioral model algorithm that predicts the customer outcome (Trusov et. al. 2016).

Predictive modeling can increase efficiency if internal user data produced from an internal platform is incorporated in the user profiles, it would make the ad recommendations even more accurate (Trusov et. al. 2016). When combining both internal data (e.g. consumer behavior data from internal product platform) and external behavior data (e.g. data from previous external paid ad campaigns), it is very important to find identifications such as device ID's (e.g. a mobile device ID that can connect a specific consumer to certain behavioral data) or other matching ID's (e.g. emails), in order to get accurate data to be used for consumer targeting (Trusov et. al. 2016). Otherwise, the consumer profile would be based on inaccurate data and thereby result in poor ad result.

A behavioral algorithm in combination with a recommendation algorithm can enhance consumer interactions with profile based ad recommendations that increase chances of consumer purchases (Trusov et. al., 2016; Yan, Liu, Wang, Zhang, Jiang, and Chen, 2009). Thus, behavioral targeting should help to increase conversion rates.

Bidding algorithms becomes very efficient in combination with a behavioral- algorithm in a RTB setting. This is because the algorithms can determine the potential worth of the individual ad impression at a specific time, through predictive modeling, and bid accordingly in real time to optimize ad conversions (Summers et. al. 2016). For instance, if a user is predicted to be more likely to convert compared to other users, the algorithms would bid higher for ad impressions towards that specific user and thus increase the chance of conversion.

The data is not always reliable and do sometimes lack information for a complete picture. Consumers use multiple devices, research online and purchase offline (ROPO) and erase cookie data. These three factors make it difficult to determine certain behavior with a unique user (Clifton, 2010). Especially for advertisers this becomes a concern since factors such as ad impression frequency becomes less controllable and accurate. On average, 33% of all online ad impressions occur after a user has already seen an ad campaign 10 times (Marketingsherpa, 2016). If the data analytics that are applied for user profiling is not correct, the information used for retargeting can lead to over-advertising and not contextual advertising (Clifton, 2010; Kieven, 2016). Contextual advertising refers to a ad that adapts relevant text based on the web page it is displayed on (Anagnostopoulos, Broder, Gabrilovich, Josifovski and Riedel, 2007). Over-advertising may involve retargeting failures such as reaching customers who have already made a purchase or a sensitive audience that can be provoked, like a man searching for a wedding ring (Pearson, 2015). This creates a problem for advertisers in general and retargeting activities in particular, because the ad results may show poor performance due to inaccurate targeting. Furthermore, If unique users can't be determined a campaign can reach higher frequency than planned. High ad frequency can create worn-out effects, which in turn contributed to lower CTR, CPC and, in worst case, negative consumer feedback (Chieruzzi, 2015).

Dynamic retargeting can control against users using multiple devices, if cross device recognition abilities is implemented in the dynamic retargeting engine. (Google, 2017a; Quantcast, 2016; Criteo, 2016c). This helps the advertisers to unify customers with multiple devices and thus increase marketing efficiency. Recommendation, bidding, behavioral and predictive targeting features will according to theory discussed above increase retargeting ad efficiencies. Therefore, we believe dynamic retargeting that base ad recommendations on consumer behavior and that predicts when it is most likely for conversion to occur, is likely to be successful. In addition, by bidding on the most likely conversion target the dynamic retargeting ad efficiency is likely to even further increase. Intelligent recommendations from sophisticated data engines is also likely to result in extra sales if ad impression takes place in the right moment of the consumer-purchasing funnel. Ultimately, this should result in an increase in ad ROI compared to not utilizing dynamic retargeting. We therefore propose the following hypothesis:

Hypothesis 3: Implementing dynamic retargeting will improve ROI

Dynamic retargeting targets customers when searching for further information in the purchasing funnel. The customer already know what kind of product he/she want to buy but are not 100% sure and thus need more information about the product(s) or service(s). This is when dynamic retargeting step in and act as a catalyst that triggers customer's willingness to come back to the company's webpage to make a purchase. The theory show that aspects included in dynamic retargeting engine, such as ad impression timing (Bleier and Eisenbeiss, 2015a), personalized ads (Lambrecht and Tucker, 2013; Court et. al. 2009), recommendation algorithm (Tonkin, et al, 2011), bidding algorithm and behavioral algorithm (Summers et. al., 2016; Trusov et. al.) have all been researched before to some degree. By investigating previous research of the subject a model (chart 2.7) of the three hypotheses was created.

Hypothesis 1: Ad impressions timing improves the CTR of dynamic retargeting
Hypothesis 2: Ad impressions timing increase consumer conversions of dynamic retargeting
Hypothesis 3: Implementing dynamic retargeting will improve ROI

The model is explaining the consumer purchase funnel and how dynamic retargeting ads fits this cycle and how it may promote CTR, CR and ROI. The dynamic retargeting ad is fueled by bidding-, behavioral- and recommendation algorithms, which we believe positively impact on ad efficiencies. Hypothesis 1 and 2 aims at explaining the impact of ad impression timing to dynamic retargeting ad CTR and CR, which is why it is part of the model.

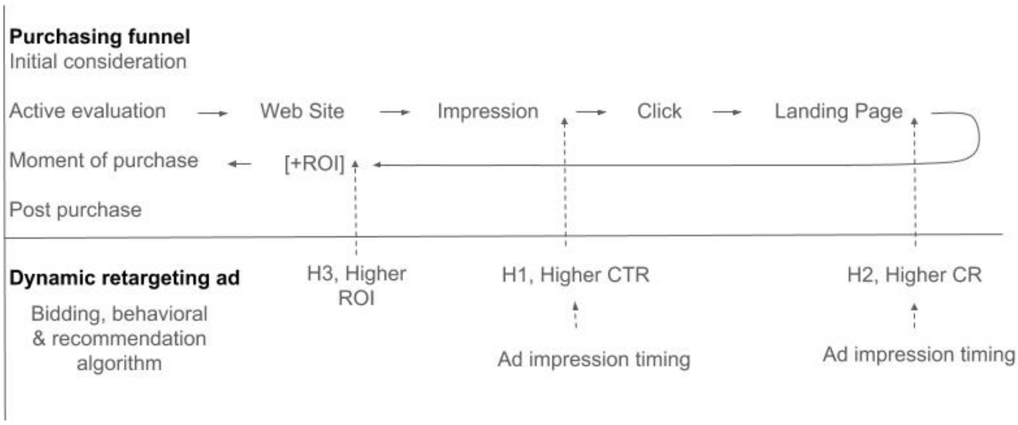

Chart 2.7: Proposed Model of Dynamic Retargeting Efficiency

3. Method

In this chapter we will describe our choice of research method and why it is suitable for our research. We will also discuss the three data sets we look at, how it was analyzed, and the company from which we received the data. We begin with explaining the technology of dynamic retargeting.

3.1 Empirical Setting

Since dynamic retargeting is rather a new concept in online advertising, we will first give an explanation of the technology and how it is used in advertising. Thereafter we give a short introduction to different companies working in this field.

Dynamic retargeting

Dynamic retargeting engines use machine-learning algorithms that learn from past efficient or inefficient retargeting actions. Thus, the engine optimizes the ad of a specific product/service to a specific target group on different platforms. Because dynamic retargeting is rather a new concept we will explain how it works:

1. Product exposure: The user is visiting a firm website but leaves without buying. During the visit a pixel tag, previously integrated on the firm website, will be automatically downloaded for each page/product the user is viewing. This information will be added to

the user profile and can later be used for retargeting purposes. The information is tracked with cookies. (Lambrecht and Tucker, 2013)

2. Targeting consumers: the user can be retargeted when browsing on a network allowing retargeting. By recognizing user cookies, retargeting companies can send out ads in accordance with the user profiles. The ad deliveries are often based from predictive and recommendation algorithms, which constantly improves from machine learning capabilities, in order to optimize ad delivery efficiencies (Criteo, 2017a). This means that ad impressions takes place when it is predicted most likely for consumer conversions, and the ad is visualizing products, based on recommendation algorithms, in accordance with user profiles. The aim is to recapture the interest of a previous browser and bring them back for valuable conversions.

3. Ad design: Depending of the type of retargeting technology, the composition of the ad differs. Generic retargeting is visualizing static broad messages, which can be triggered based on previous visits of a company homepage (Lambrecht and Tucker, 2013). In the case of dynamic retargeting, the engine includes algorithms that learn on their own to maximize the efficiency based on previous consumer behavior. The design in dynamic retargeted ads is high in personalization and change in real time based on what products the individual customer browse on the firm's website. The dynamic retargeted ad is able to include whatever images from products that are in line with the user profile and dynamically compose the ad in whatever way that the algorithm finds most engaging (Criteo, 2017).

4. Purchase: When the customer click on the banner they are transferred to the firm website where conversion is the goal. The retargeting will thereafter stop until new recognized interest triggers the dynamic retargeting engine (Lambrecht and Tucker, 2013).

5. Business model: It is most common that the firm pay the performance company that provides the retargeting engine cost-per-click (CPC), which depends on the CPM (cost per thousand impression) publisher price, the CPM bid and the amount of clicks being

generated. Thus, the firms providing retargeting technology buy on CPM from online publishers and sell clicks to advertisers. The retargeting engine is optimizing according to the key performance indicators (KPI) that the advertisers asked for. KPI's could be; in-app/website purchases, online registrations or increased volume in online purchasing baskets.

The dynamic retargeting industry is complex to research and understand in regard to that it is very secretive. The algorithms used to analyze the data are the main advantage for each firm and thus they want to protect it. We started out our research by wanting to understand how the algorithms between the different firms differed from each other to enable an understanding for the phenomena and a common term for it.

Third-party platforms such as AdRoll, Perfect Audience and ReTargeter all provides a platform for retargeting ads and to handle technical components as cookie-data (Baker, 2015). Retargeting have a great opportunity to help consumer to purchase, but, some retargeting failures like over-advertising may have a negative impact on consumer behaviors. Therefore, performance-marketing companies is constantly trying improve their retargeting technology, in order to make it more intelligent and better fit the consumer purchasing funnel.

Performance marketing company Sellpoints, giving it an advancement with behavioral data across 150 of the biggest online retailers, bought ReTargeter in 2015. The data is stated to increase their predictive analytical capabilities (ReTargeter, 2015). This is a common theme in digital marketing in general and retargeting technology in particular, where consumer insights from data are key for successful advertising.

Quantcast (2016) is company that provides a third party data intelligence platform that help other companies with gathering of consumer behavior data and predictive analytics with the goal to better understand and get target consumers to convert from retargeting (Quantcast, 2017). Quantcast guarantees data quality with own technology but also use DoubleVerify. DoubleVerify (2016) describe themselves as a firm that help third-party platforms to ensure data accuracy by improving the quality of each ad impression and controlling for cross screen view ability (devices and platforms), fraud and geographic area.

Google retargeting added in 2014 "Smart Lists" that is described as a remarketing algorithm based on machine learning (Marvin, 2014). The algorithm calculates which consumers that are most likely to convert using a recommendation algorithm (Google, 2017d). Criteo is another retargeting based company that states to use a recommendation-, a behavioral-, and a bidding algorithm. These algorithms are fueled by machine learning capabilities for constant improvement over time (Criteo2, 2016; Criteo3, 2016). However, from an efficient market hypothesis it is probable that all firms use the same kind of technology, to some degree, and thus we describe dynamic retargeting from the standpoint of both Google and Criteo that describe the phenomena in a more thorough way.

3.2 Research Approach

We explored the known phenomenon dynamic retargeting and tested how the phenomenon matched with current theory. From our literature review we built hypotheses that we tested based on validity in a given circumstance that the data was limited to (Snieder & Larner, 2009). Thus, we used a deductive approach with the aim to answer the three hypotheses described in the theory section (Saunders, Lewis & Thornhill 2009; Snieder & Larner, 2009). This is a quantitative research focusing on data that will be transformed into useable statistics. We choose a quantitative approach because we wanted to investigate dynamic retargeting efficiency and be able to generalize results to theory (Saunders et. al., 2009, Bryman & Bell, 2011). The data consist of large samples from three separate companies and will be used to generalize results based on multiple dynamic retargeting campaigns.

3.3 Research Company & Data

All data in this study is gained from performance marketing company Criteo. The company was founded in 2005 and have today 2500 employees worldwide, $550 billion in sales transactions (from companies utilizing Criteo dynamic retargeting) analyzed in 2016 and above 900 billion ads served the same year (Criteo, 2017b). Criteo fiscal year revenue in 2016 was $1.8 billion (Criteo, 2017c). Their primarily product is a dynamic retargeting engine. Criteo engine include both cross device recognition, recommendation-, bidding- and behavioral algorithms optimizing dynamic retargeting campaigns, which constantly improves through machine learning capabilities. Criteo have a market share in the retargeting industry of roughly 8%, based on Alexa index. However, the index does not account for dynamic retargeting specifically, but it gives a rough estimate of the size of Criteo in the market, which includes both Google and Facebook (Datanyze, 2017).

In this study we used data from three different data sets. The first set consist of data from a dynamic retargeting campaign made for a Swedish electronic retailer, the second data-set from a campaign for a Danish electronic retailer and a third data set from a Finnish online classified ad company. All numbers we present use commas as thousand dividers and dots for figures below zero.

3.3.1 Swedish Retailer Data Set

In the case of the Swedish retailer we did analysis between two groups that was exposed for dynamic retargeting but with different delays of the dynamic ad impressions. This analysis statistically tests differences on CTR and conversion rate (CR) when taking ad impression timing into consideration.

In this test the group called “Direct” were targeted with ads directly after site visit, and the group called “8-hour delay” were targeted with ads after 8-hours. The number of exposed users can be seen in table 3.4.1. This is the amount of unique users that was exposed for dynamic retargeting ads out of the total target audiences in this test. Impressions show the total amount of ad impressions of the exposed users. The statistical tests used for analyzing data was a Z-test to test whether proportions out of sample sizes are significantly different, which is recommended by Campbell (2007) and Richardson (2011). The data collection period was during 20 days in November 2016.

Table 3.3.1 - Test size - Swedish retailer

Group	Audience	Exposed Users	Impressions
Direct	715,975	101,558	1,417,125
8-hour delay	685,308	96,160	1,268,442

3.3.2 Danish Retailer Data Set

The case with the Danish retailer shows the effects on ROI when implementing dynamic retargeting. In this test, one group was exposed for dynamic retargeted ads and the other group was a control group not exposed for dynamic retargeting ads. We statistically test differences in revenue per user (RPU) between the two groups, in order to determine the incremental ROI (iROI), which is the incremental revenue divided by the advertising costs. Incremental revenue is calculated with the following calculation: (RPUexposed - RPUcontrol) x UUexposed (Unique users in the exposed group). This is the extra income that is generated by utilizing Criteo dynamic retargeting. Under the null hypothesis we can consider no difference between the groups and since we didn't know the probability distribution of RPU difference, we applied permutation test method (Fisher, 1935; Pitman, 1937) in order to be able to determine significant results in the differences of RPU between the two groups.

In table 3.3.2 the sample sizes for this test can be seen. In this test the number of unique users is based on an unique cookie ID. The column "Buyers" shows the amount of buyers out of the total amount of unique users analyzed in this test. The data collection period was approximately 30 days between October and November 2016.

Table 3.3.2 - Sample sizes - Danish retailer

Group	UU	Buyers
Exposed	79,982	2,227
Control	75,988	1,858

3.3.3 Finnish Classified Ad Site Data Set

This data shows the path between impression devices (desktop, smartphone and tablet) before the purchase is done. By analyzing this data, we will get insights on the importance of cross-device recognition abilities in retargeting engines, in order to optimize cost-efficiencies, ad deliveries and finally conversions. The data was analyzed and compiled using Excel, which was an efficient way of getting overview of the path to purchase among consumers. This also gave us the opportunity to create charts for visual presentation of the path to purchase. The total amount of purchases in table 3.3.3 is the size of the data sample.

Table 3.3.3 - Finnish Classified Ad

Group	Amount of purchases
Total	18712
Desktop	10052
Smartphone	6366
Tablet	2294

3.3.4 Reliability & Validity of Data Sets

The data we received from Criteo was complete with the entire tests data. Thus, they didn't give us chosen samples, which could be data with, for instance, specifically high CTR or CR. In both the Swedish & Danish retailer datasets the audience size, exposed users and impressions is similar in sizes of the two groups. This gives more accurate comparisons since major differences often have considerable effect on performance metrics. Furthermore, since the cookie-pool was split 50/50, faster result stability was enabled, which is getting observed sample results large enough to gain reliable test results. This also minimizes external factors to influence the test results.

The data testing for the Swedish retailer and the Danish retailer was based on incremental A/B tests, in order to increase data reliability and validity by avoiding seasonality differences or other affecting variables to the two groups tested in each test. An incremental A/B test is parallel testing between two groups, giving one group test treatment and the other not, in order to being able to measure the uplift/decrease of treatment effect between the groups (Siroker and Koomen, 2013). However, the test length was approximately a month, which need to be taken into consideration when evaluating results (Patel, 2013). For instance, different times of the year may influence results differently

The target KPI's was also clearly decided before data was collected, algorithms was optimizing towards target KPI and test success or failure was clearly determined (Siroker and Koomen, 2013). Therefore, data measurement can be considered valid since there were no doubt which KPI that should be measured.

In the Danish retailer case a data-cleansing period was also performed. This is to ensure a clean cookie pool of the control group by minimizing delayed effect of dynamic retargeted ads in consumers' minds (Siroker and Koomen, 2013). The cookie pool is the amount of unique cookies that was included in the test. This cookie pool was split 50/50 to be able to expose half of the users to dynamic retargeting ads and the other half could function as a control group not exposed. The cleansing period was seven days before result measurement started and, seven days before the test ended, new users was not added, in order to give all users a seven day post click conversion window. Furthermore, outliers (>99th percentile) were replaced (with the 99th percentile) since they are not representative of normal user behavior.

The Finnish classified case can be considered to have reliable data, since the different devices from which product browsing and purchases was made from, is recorded in Criteo data system with their unique device ID’s.

3.4 Connection Between Data Sets and Hypotheses

Hypothesis 1: Ad impressions timing improves the CTR of dynamic retargeting
Data set: Swedish Retailer, CTR test.

Hypothesis 2: Ad impressions timing increase consumer conversions of dynamic retargeting
Data set: Swedish Retailer, CR test

Hypothesis 3: Implementing dynamic retargeting will improve ROI
Data set: Danish Retailer, ROI-test

Extra data - path to purchase - cross device recognition
Data set: Finnish Classified Site

4. Result Analysis

In this chapter we present the results from testing our hypothesis. Additional campaign results from each data set are also presented to give a comprehensive picture of the entire campaigns. The statistically tested hypothesis will then be discussed together with this paper theoretical framework in the following discussion chapter.

4.1 Swedish Retailer Data Set

The Swedish retail company ad-campaign results shows that it is more effective to directly target dynamic retargeting ads without any delay. In table 4.1.1 the size of the campaign is presented, where “Audience” represents the total size of the target group, “Exposed Users” is the number of users out of the audience size that was exposed to dynamic retargeting ads. “Impressions” is total amount of times the ads was visualized. On average the group "Direct" had an ad frequency (impressions / exposed users) of nearly 14, meaning that each user saw an dynamic retargeting ad 14 times. The group 8-hour delay had an ad frequency of 13. Thus, the ad frequency is almost the same between the groups, which makes comparisons more reliable. Table 4.1.2 shows the total campaign results and table 4.1.3 shows key ratios that highlight ad efficiencies.

Table 4.1.1 - Test size - Swedish retailer

Group	Audience	Exposed Users	Impressions
Direct	715,975	101,558	1,417,125
8-hour delay	685,308	96,160	1,268,442

Table 4.1.2 - Test result - Swedish retailer

Group	Clicks	Sales	Revenue (SEK)	Cost (SEK)	ROI = (Revenue - Cost) / Cost
Direct	20,822	1,237	2,121,801	36,685	56.8 x investment
8-hour delay	18,014	929	1,546,904	32,000	47.3 x investment

Table 4.1.3 - Key ratios - Swedish retailer

Group	CTR	CR	CPC
Direct	1.47%	5.94%	1.76 SEK
8-hour delay	1.42%	5.16%	1.78 SEK

In the first test we tested the CTR level differences between the two groups. In this test CTR is the proportion out of the population "impressions" that is compared between the two groups. The test results show significant differences, with a Z-Score of 3.4262 and a p-value of 0.0003 ($p < 0.01$), which means that the Direct group has significantly higher CTR of 1.47% compared to 8-hour delay group CTR of 1.42% (Campbell, 2007; Richardson, 2011). Therefore, we reject the null-hypothesis and states that there are significant better CTR if the ad impression occurs directly after browsing products. *Hypothesis 1: Ad impressions timing improves the CTR of dynamic retargeting* has support.

In the second test of the Swedish retailer data set we tested the CR difference between the two groups. CR is the proportion out of the population "clicks". The CR difference is between the sample sizes significant with a Z-Score of 3.3401 and a p-value of 0.00042 ($p < 0.01$) (Campbell, 2007; Richardson, 2011). This means that CR in the Direct group is significantly higher than the CR in the 8-hour delay group. We therefore reject the null-hypothesis and states that the CR goes up if the ad impression occurs directly after browsing products. *Hypothesis 2: Ad impressions timing increase consumer conversions of dynamic retargeting* has support.

In the Swedish dataset we found that an dynamic ad campaign that retargeted directly users had better performance compared to the ad campaign with 8-hour delay. Compared to the Direct group, the 8-hour delay group had a CTR that was 3.4% lower, CR was 13.1% lower and ROI that was 16,7% lower. On an average month*, the Swedish retailer had 18,700,000 impressions, 170,000 clicks and a budget of 377,000 SEK. This means, the direct display of banners instead of 8-hour delay would result in extra: 9,350 clicks, 1,326 sales and 3,581,500 SEK in profit (see table 4.1.4 for calculations).

*Based on numbers between January - October 2016 of the Swedish Retailer

Table 4.1.4 - Calculations Swedish retailer. Difference refers to the difference between the two groups.

Impression 18,700,000 * CTR-difference of 0.05% = 9,350 clicks	Clicks 170,000 * CR-difference of 0.78% = 1,326 sales	Spend 377,000 * ROI-difference of 9.5x investment = 3,581,500 SEK profit

4.2 Danish Retailer Case

The results from this test can be seen in the table 4.2.1-4.2.3. What we can see is that the buyer rate and transaction rate has a respectively +16.7% and +13.6% uplift in the group exposed for retargeting ads. The average order value is -8.2% worse in the exposed group.

Table 4.2.1 - Buyer rate

Group	UU (unique users)	Buyers	Buyer rate	Uplift
Exposed	79,982	2,227	2.8%	+16.7%
Control	75,988	1,858	2.4%	

Table 4.2.2 - Transactions per buyer

Group	Transactions	Buyers	Transactions/Buyers	Uplift
Exposed	4,282	2,227	1,92	+13.6%
Control	3,145	1,858	1.69	

Table 4.2.3 - Average order value (DKK)

Group	Transactions	Order value	Order value/transactions	Uplift

Exposed	4,282	15,348,211.0	3,584.6	-8.2%
Control	3,145	12,281,465.6	3,905.1	

However, the main purpose with this test is to statistically ensure the iROI by statistically test differences in RPU (table 4.2.4). The difference in RPU between the groups is 30.3 (30.272). By applying permutation test we re-sampled our data 5,000 times and got 5,000 new simulated RPU differences, with a distribution under the null hypothesis visualized in chart 4.2.5.

Table 4.2.4 - Revenue per user (DKK)

Group	UU	Revenue	RPU	Uplift
Exposed	79,982	15,348,211.0	191.9	+18.8%
Control	75,988	12,281,465.6	161.6	

The amount of simulated RPU differences above 30.272 out of the 5,000 becomes our simulated p-value, which determine significance (Fisher, 1935; Pitman, 1937). After running the test we got observed difference in means: 30.2720620839 with bootstrap empirical P-value one sided: 0.0. The RPU difference between the groups is significant ($p \leq 0.01$). We can thereby reject the null-hypothesis and statistically ensure that the RPU of group "Exposed" is significantly higher than the group "Control".

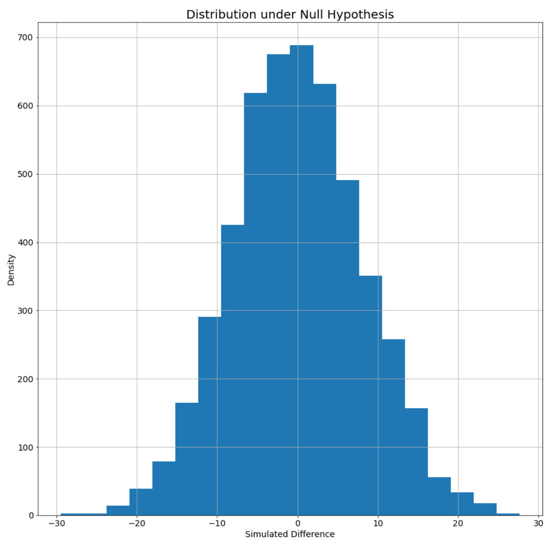

Chart 4.2.5 - Histogram: RPU distribution under null hypothesis

In table 4.2.4 the results in terms of iROI can be seen (see table 4.2.5 for calculations). Since the RPU difference is statistically ensured and is the only thing in the iROI calculation (table 4.2.5) that varies between groups and need to be tested, we can state that the iROI of 62,3 * investment is significant. *Hypothesis 3: Implementing dynamic retargeting will improve ROI* is thereby supported.

Table 4.2.4 - ROI (DKK)

Incremental RPU	Incremental income	Spend	Incremental ROI
30,3	2,423,454,6	38,880,6	62.3 x investment

Table 4.2.5 calculation incremental ROI

iROI
=
RPU difference 30.3 * UUexposed 79,982
/
Spend 38,880.6
=
62.33

4.3 Finnish Classified Ad Site

In chart 4.3.1 the path to purchase is visualized from the observed 18,712 purchases (table 3.3.3). The inner circle shows on which device the purchases occurred. The outer areas are visualizing additional device touch points. For instance, the white area means no additional touch points and if the same color occurs that means the same type of device (same environment) but another one. An example: from the inner blue circle; if the next areas is orange, blue and grey, that means; before the purchase on desktop the user browsed products with a smartphone, another desktop and a tablet, in that specific order.

The main result out of the path to purchase analysis is that 72% of buyers used at least 2 devices and switched at least 3 times before the purchase. This highly recommends cross device recognition as something very important in ad retargeting. Otherwise, inefficiencies in terms of costs, ad deliveries and finally conversion rates would greatly decrease. This is because retargeting algorithms “start over” on the other devices since they would behave as the target user is a new unique user. More important insights are presented below in table 4.3.2.

Chart 4.3.1 - Path-to-purchase

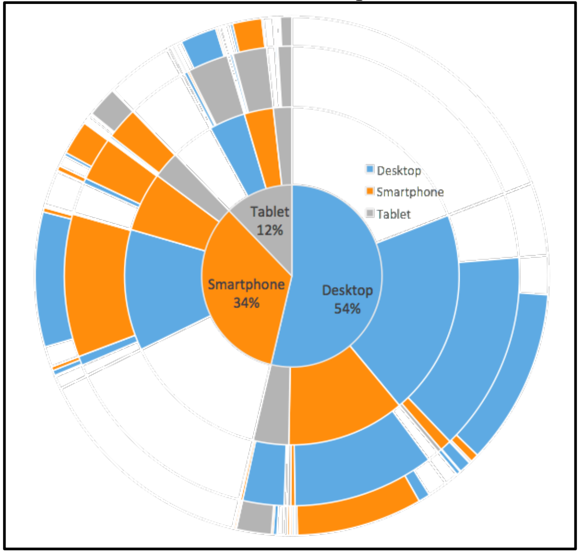

Table 4.3.2 - Path-to-purchase

Environment variety

- 54% of recorded sales on desktop
- 34% of recorded sales were made on smartphone
- 12% of recorded sales were made on Tablet

Multiple devices

- 63% of buyers browsed the website with another device before the sale
- 64% of Desktop buyers browsed the website on at least another device before the sale
- 58% of Smartphone buyers browsed the website on at least another device before the sale
- 66% of Tablet buyers browsed the website on at least another device before the sale

Multiple device, same environment

- More than 17% of Smartphone buyers used 2 different Smartphones for browsing (6% overall)
- More than 37% of Desktop buyers used 2 different Desktops for browsing (20% overall)
- More than 15% of Tablet buyers used 2 different Tablet for browsing (2% overall)

Multiple device, multiple environment

- More than 26% of buyers used both Desktop and Smartphone devices in their path to purchase
- More than 36% of Smartphone buyers used a Desktop before the sale
- More than 33% of Tablet buyers used Desktop before the sale

5. Discussion

In this section we discuss our findings from result analysis and link them to this paper theoretical framework. After we present our theoretical contribution to retargeting advertising, we discuss managerial implications, study limitations and recommend areas for future research. We then conclude with a research conclusion.

5.1 Dynamic Retargeting Impact On ROI

The purpose with this paper was to investigate the efficiency of the relatively new marketing phenomenon dynamic retargeting through answering the following research question: *How does dynamic retargeting influence consumer ad engagement and purchasing behaviour?* In order to answer the research question we formed three hypotheses based on previous research regarding retargeting in general and more specific features that characterizes dynamic retargeting, such as ad personalization. We got support for all our hypothesis and we will discuss them starting with hypothesis 3: *implementing dynamic retargeting will improve ROI,* which we believe is the most important finding in this paper.

Previous research conclude that integrated recommendation and behavioral algorithms can create more relevant recommendations to the user (Summers et al, 2016; Corbellini, et al, 2016; Manjula, and Chilambuchelvan, 2016; Hu and Pu, 2011; Hu and Pu, 2010; Tkalcic, Kunaver, Tasic and Košir, 2009) and thus enhance consumer interaction and increase the chance of consumer purchase (Trusov et. al., 2016; Yan, et al, 2009). Furthermore, behavioral algorithm can together with a bidding algorithms target the most likely consumer to convert and thus increase or decrease ad impression bids depending on the prediction (Trusov et. al. 2016). Our findings support previous literature with increased consumer interaction from an ad targeted with behavioral-, bidding- and recommendation algorithm, as dynamic retargeting possess these types of algorithms. We recognized an increase in both the buyer rate (16.7%) and transaction rate (13.6%) from dynamic retargeting compared to users who made purchases without clicking in from a dynamic retargeting ad.

Our main finding is the statistically ensured iROI of 62.33 times the investment for user exposed to the dynamic retargeting ad compared to users not exposed. This testifies not only about the superior advertising efficiency of dynamic retargeting, it also shows incremental effect, the extra value, dynamic retargeting is able to trigger among each individual buyer. Thus, dynamic retargeting may be seen as something more than simple advertising, perhaps it should be evaluated as a new efficient income stream? Utilizing efficiently, dynamic retargeting can maximize income from buyers and help businesses to expand more quickly. However, even though the figures of iROI 62.33 times the investment can be considered as very good and support that dynamic retargeting is something very lucrative, the results must be evaluated with criticism. In the Danish retailer case where iROI was tested, the investigation was based on data from a online electronics retailer. The income per product was perhaps rather high compared to other product categories, which may resulted in unusual high RPU, which the calculation of iROI is based on. Furthermore, to really understand the impact that dynamic retargeting may have on the entire business operation, extra calculations with the profit determining the iROI should be made.

In the case with the Swedish retailer the statistically ensured CTR and CR had an impact on the ROI, the direct display of dynamic retargeting banners led to an increase in ROI of 9.5 times investment compared to delaying ad impressions. This is an extension to previous literature (Bleier and Eisenbeiss, 2015a; Breuer et. al., 2011), by adding timing as a factor to ROI. However, we did not statistically ensure the ROI difference, but the statistically ensured difference in CR between the group direct and 8-hour delay would result in an extra 1,326 sales on an average month, which would affect ROI positively.

5.2 Dynamic Retargeting Impact On CTR & CR

We believed timing to be essential in dynamic retargeting, because results is likely to be better when potential customers have products they browsed fresh in memory.

Our first hypothesis: *Ad impressions timing improves the CTR effect of dynamic retargeting* and second: *ad impressions timing increase consumer conversions of dynamic retargeting,* are statistically tested and have support. It give weight to the importance of timely reaching customers in their evaluation stage (Court, et al 2009). If the user have, after leaving the browsing website, not completed his or her conversion, the direct display of dynamic retargeting ad will increase ad CTR with 3.4% and CR with 13.1% compared to delaying the dynamic ad retargeting. Dynamic retargeting can thus help the firm control the consumer-driven message on the internet, due to banners are shown on places where conversions is likely to happen. It could be when customer are searching for product reviews, reading articles about the specific product or when they browse social media after browsing company homepage. The consumer-driven messages is very important, because it impact the choice of ⅔ of the brands that is added to the active evaluation stage in the consumer purchase funnel (Court et. al, 2009).

Our result regarding ad CTR reinforce current research. Bleier and Eisenbeiss (2015a) found that a personalized ad is most effective when the customer recently visited the company website. Their study also conclude that personalized retargeting have higher CTR when the ad is targeted directly. This is also recognized by Breuer et. al. (2011) who found that ad CTR performance ended within one day and was better directly after browsing products. Our research also extends their research with adding that the CR is higher when a dynamic retargeting ad is targeted directly. We found that the CR 13.1% higher when target consumers directly after browsing products. This result is reasonable due to consumers is constantly bombarded with information and therefore ad results is likely to be better when ads visualize promotions of something the consumers have fresh in memory.

Customers have very specific needs and want the ad targeted at the right time in the purchasing funnel when it is helpful for them. Therefore, dynamic retargeting that considers timing will improve ad efficiency and minimize ad targeting that otherwise would be intrusive (King and Jessen 2010; White, Zahay, Thorbjornsen and Shavitt, 2008). By increasing the fit of the ad impression through timely accurate ads in the consumer-purchasing funnel, it is likely to increase ad conversions according to our study.

5.3 Dynamic Retargeting & Cross Device Recognition

We found that 72% of buyers used at least 2 devices and switched at least 3 times in their path to purchase. This highlights the problem with many of today's banner and retargeting ads that do not control for cross-device usage. Without cross device recognition ability, the marketer is blind and can not calculate ad impression, frequency or conversion correctly. This creates problems such as over-advertising and not contextual advertising (Clifton, 2010; Kieven, 2016) and negative customer complains (Chieruzzi, 2015; Pearson, 2015). In the extension this affects advertising costs due to ad inefficiencies. It may also negatively impact the whole brand. Furthermore, by being able to recognize users across devices, a better understanding of the consumers purchasing funnel will be possible. This will inturn help dynamic retargeting algorithms to optimize their ad distribution scheme and better fit the consumer purchasing funnel.

5.4 Theoretical Contribution

Our main contribution to retargeting theory in general and dynamic retargeting in particular is the ROI measurement in advertising. We could not found this type of measurement from previous research, which mainly explained ad efficiency regarding the ad in itself, not so much about post click behaviour and nothing about ROI. This is probably because of company protectiveness of their consumer data, which result in poor access to these kind of data.

In addition we reinforce previous research about how ad impression timing impacts CTR (Bleier and Eisenbeiss, 2015a, Breuer et. al., 2011) by adding electronic retailer in the explored businesses that utilize retargeting. We also extend this research by adding how CR and ROI is affected by ad impression timing.

We also contribute with knowledge about cross device recognition, which is important because of the impact on the consumer purchase funnel and that dynamic retargeting with cross device recognition ability may help to solve some of this issues.

Furthermore, the dynamic retargeting technology that we investigated could not be found in other research and therefore contribute to the current retargeting research, by adding dynamic retargeting with bidding-, behavioral- and recommendation algorithms. Our theoretical contribution can be summarized with a revised dynamic retargeting model (chart 5.4). This model added ad impression timing, to the proposed model (chart 2.7), as a factor that promotes ad ROI.

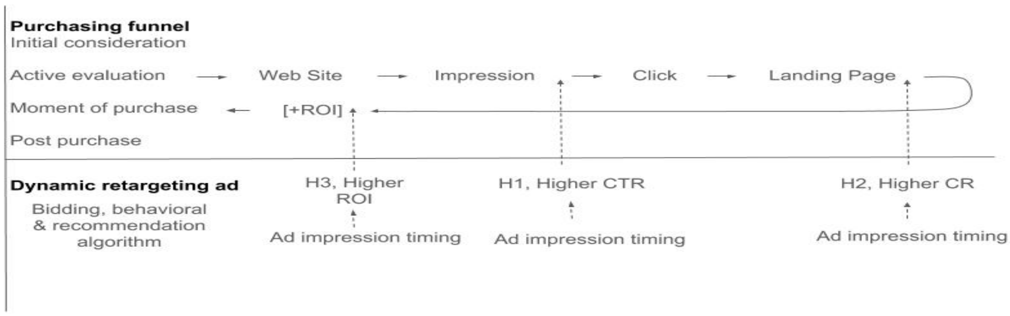

Chart 5.4 - Revised Dynamic retargeting model

5.5 Managerial implications

By being able to measure online ad efficiencies all the way to ROI can change the entire culture around marketing in some companies. For instance, our analysis show that dynamic retargeting is triggering consumer behavior that result in RPU of SEK 191.9 compared to SEK 161.6 among users not exposed. Thus, if further research show similar result as this study, it can convince marketers of the efficiency of dynamic retargeting and therefore create higher investments in the dynamic retargeting technology. This can lead to a marketing culture shift, from a brand- to a financial result orientation in some industries. This sets demands on practitioners to better understand retargeting technology and the optimal way of implementing it to their specific business. Our revised dynamic retargeting model (chart 5.4) could be used as visualization to practitioners about the connection between the consumer purchase funnel and dynamic retargeting effectiveness.

We found in previous literature that some marketers avoid using retargeting because of the potential negative impacts such as multi device issues and inaccurate marketing messaging (Handley and Lucy, 2016; Nottorf, 2014). Therefore, we also wanted to investigate if dynamic retargeting is more effective in preventing potential negative impacts from happening. Our data analysis of cross device recognition suggest that dynamic retargeting that have this ability help minimize the negative impact of multi-device usage and inaccurate marketing messaging by unifying users across their multiple devices. This insight is something that is helpful to practitioners in order to be able to control for over-advertising and contextual advertising in regards to the consumer-purchasing funnel. If the users can be recognized across their devices, contextual advertising will be easier due to algorithms can distribute ads in accordance with consumer's status in the purchasing funnel.

5.6 Limitation

The data we analyzed was limited to one time period and behavior may change with seasonality, for instance can the weather influence smartphone behavior and thus the ability to influence consumer with dynamic retargeting. The tests did also overlap with other marketing effort, which influence the results of dynamic retargeting.

The CTR, CR and ROI results is limited to the retail sector within electronic. The ad impression timing test was limited to the time horizon of eight hours, so any further awareness, engagement and or impacts on other marketing channels, was not measured.

Our cross device recognition data was only showing the path of purchase without testing two groups were cross device recognition was enabled and disabled, in order to recognize ad efficiencies utilizing this ability. Thus, we could not draw any extensive conclusions from the cross device recognition analysis.

5.7 Future Research

Dynamic retargeting is only one way in helping customers to reach a decision in their purchase funnel. Other strategies are search engine optimization (SEO) search engine marketing (SEM) and app-marketing. Further research in how these kind of marketing activities in combination with dynamic retargeting can co-produce higher consumer value and generate higher ROI is worth investigating. With a deeper understanding, theoreticians may help practitioners in the development of products that connects the whole marketing funnel, from initial consideration to closure and post-purchase consideration. These kind of tailored complete marketing solutions for individual companies is likely to be highly requested.

Future research should also look more into cross device recognition and perform AB test where cross device recognition is enabled among one group and disabled at the other. Understanding this more thoroughly may help retargeting strategy to become even more efficient and minimize ad intrusiveness. Furthermore, by categorizing certain products and find correlation between product category and consumer feelings of intrusiveness, important knowledge regarding which businesses that are suitable for dynamic retargeting will be found. It may also help to find a solution of how to solve these issues by specific tailored solutions for sensitive product categories, such as wedding rings which you do not want to be retargeted if you share computer with the potential wife/husband.

We found that dynamic retargeting generates high ROI. However, single cases does not make something completely true. Future research should focus on comparing different product categories and services, in order to recognize differences in ROI possibilities with dynamic retargeting.

Finally, retargeting have to some degree customer trust issues among less trusted brands. Based on the degree of ad personalization, less trusted brands have a decreased CTR with 46% (Bleier & Eisenbeiss, 2015b). Therefore, it is important to take this into account, especially for smaller firm's or not well known brands. This is also a research topic that could be further explored. We know that dynamic retargeting change degree of personalization for each individual, but do the change of personalization also affect the degree of brand trust? And if so, how can dynamic retargeting solve this problem?

6. Conclusion

Our research question was *how does dynamic retargeting promote consumer ad engagement and purchasing behavior?* Based on our research it can be considered answered, due to our results which highlights both efficiencies of the ad itself but also what it generates in terms of purchases and ROI. Our findings support previous literature that ad personalization and timing will affect consumer engagement, efficiency and also their purchase behaviour, positively affecting ROI. We found that dynamic retargeting that also consider timing (in this case, ads targeted directly after browsing instead of 8-hour delay) had 3.4% higher banner click-through rate and a conversion rate that was 13.1% higher. We also found that dynamic retargeting is increasing ROI. Our results show that dynamic retargeting had a iROI of 62.33 times the investment. Lastly we recognized the importance of being able to recognize users across different devices. We found that 72% of buyers used at least 2 devices and switched at least 3 times before the purchase, which highly suggest cross device recognition as an important feature in dynamic retargeting, in order to gain efficiency in ad delivery, costs and results.

Dynamic retargeting may be the holy grail in marketing, by enabling personalized product offerings to every visiting consumer. However, data accuracy is something that have created uncertainties regarding the actual efficiencies with retargeting technology in the past and is something that constantly need to be developed in order to improve transparency of the data and the actual user. Upcoming issues regarding this matter could be data protection laws, which may hinder possibilities for utilizing data the way dynamic retargeting does. If this can be handled without major problems, dynamic retargeting is likely to flourish even more, due to predictive personalized targeting, which gives the digital consumer what he/she wants when he/she wants it.

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