The Improvement of Retargeting by Big Data: A Decision Support that Threatens the Brand Image?

Mercanti-Guérin Maria

Assoc. Prof. Dr., Université Paris 1 Sorbonne

Abstract

With the emergence of Big Data and the increasing market penetration of ad retargeting advertising, the advertising industry's interest in using this new online marketing method is rising. Retargeting is an innovative technology based on Big Data. People who have gone to a merchant site and window-shopped but not purchased can be re-pitched with the product they showed an interest in. Therefore, click rates and conversion rates are dramatically enhancing by retargeting. However, in spite of the increasing number of companies investing in retargeting, there is little academic research on this topic. In this paper we explore the links between retargeting, perceived intrusiveness and brand image. As results show the importance of perceived intrusiveness, ad repetition and ad relevance, we introduce new analytical perspectives on online strategies with the goal of facilitating collaboration between consumers and marketers.

Keywords: big data, retargeting, perceived intrusiveness, ad relevance

Introduction

Behavioral targeting is a technical analysis of people behavior, and as a consequence a technical analysis of target. It is based on the latter's past consumers behaviors and provides tailored proposals for individual needs and expectations. Behavioral targeting includes a multitude of techniques and types of ads. In this highly competitive market, a technique called retargeting seems to be the Promised Land for advertisers. Indeed, while the estimate clickthrough rates do not exceed 0.1%[1], retargeting (also known as remarketing) improves conversion rates [2] by 5 and 10%. Retargeting keeps the brands in front of bounced traffic after consumers leave the website without purchasing. These "visitors" so-called bounced visitors are, then retargeted *via* dynamic creative (also known as personalized retargeting), which allows an advertiser to display a banner created on-the-fly for a particular consumer based on specific pages and requests. Advertisers customized and optimized real-time messages that follow consumers from site to site until the bounced visitors return to the e-commerce site to complete their order or sales funnel. Companies like

Criteo ensure to retarget and re-engage 90% of these bounced visitors in the 24 hours that followed their visit and display these ads on more than 4,000 partners sites (editors). Retargeting is based on intensive use of Big Data that extend retargeting to e-mailing and predictive analysis. This extreme customization of the offers is a great help to decision making for businesses because it allows to "push" the offers that are most likely to generate sales. Retargeting reshapes in a very efficient way advertising creation, product claims, promotional campaigns and the detection of key segments. However, these techniques are regarded as intrusive by users and forced people to adopt ad avoidance strategies (clear cookies after a visit, sites avoidance…). The objective of this research is to assess the consumers acceptance of this form of communication and, beyond the strict efficiency on sales, the impact of the retargeting on brands image. In a first part, we will detail what bring Big Data to retargeting and, more generally, what decision support Big Data represent. We will describe, also, the eco-system that addresses infrastructure and investments focused on these advertising field. In a second part, we present the results of research conducted on 200 consumers on their perception of retargeting. In the third part, we will discuss the results of the study and the possible impact of the use of Big Data on brands image and the efficiency of retargeting.

The contributions of Big Data in e-commerce: from business intelligence to retargeting

A "data intelligence" become impossible?

Big Data are difficult to define. They derive their origins from academic unpublished works of John Mashey and others belonging to Silicon Graphics[3] in the mid 1990s. The first academic reference published on Big Data comes from Francis X. Diebold (2000), today considered as the founder of the academic reflection on Big Data. He said that he had been strucked as many of these colleagues by the new statistical potentials offered by these recent extensive data. These capabilities were even criticized by some academics including Sala-I-Martin (1997) making fun of the two millions of regression that it was possible to do with Big Data. The current dynamic factor models (or *Dynamic factor models* for DNF) dispense with many statistical tests, including the classic approach based on probabilities (Reichlin, 2003). Moreover, as pointed out by Dieblod (2000), Big Data are built on an academic vision rather than a business vision. Big Data are special data (Huggett, 2020). This is evidenced by the importance of IBM supercalculators or the influence of major IT consultancies as the Gartner in the definition and further reflection on Big Data. Therefore, Diebold (2012) is considering Big Data from two perspectives :

Big Data as a phenomenon affecting the entire scientific assets and business of the company. Thus, the Big Data size evolves according to the sectors and is growing exponentially. What was considered satisfactory in terms of size and provision of information is regarded as insufficient the next month. Several reflections are carried out to define the concept of data life cycle in the field of management (Kim and al., 2020 ; Simonet, 2012).

Big Data as an emerging discipline. Diebold (2012) underlines the large areas taken over from other branches as computer science, information systems, econometrics and statistics. He concludes that Big Data are a perfect illustration of an "interdisciplinary" discipline. More recently, Stitzlein and al. (2020) provide an overview of the influence of big data in a multidisciplinary perspective.

For digital marketing, Big Data are coming to revolutionize the knowledge and management of customer relationship, through Business Intelligence and data analysis. Indeed, they bring an immediate monetization to e-commerce sites. However, their implementation in the heart of marketing strategies has not been immediate (Ghasemaghaei et al., 2020). Chen, Chiang and Storey (2012) or Ziliani (2019) detail the steps that led businesses to reconsider their approach to markets and customers in light of Big Data. Business Intelligence-1.0 was the first step in discovery the Data as a market. These customer data have been structured and collected by companies and then stored and analyzed in RDBMS for *relational Database management systems.* Datawarehouses relied on tools of extraction, transformation and loading of data collected in compliance with all legislations based on relevant existing laws. These tools provide consumers rankings and data viz (from the inactive customer through the hot prospect). These scores were based on multiple statistical and technical datamining methods: classification, regression, segmentation, predictive models... The so-called Business Intelligence 2.0 was brought by the Web. A mass of data could be gathered on the Internet through search engines and the pioneers of e-commerce. These data have a number of characteristics often summarized in terms of the 3 V namely volume, variety of sources and velocity (extreme and continuous growth). They have to grow exponentially with users generated content (UGC). Indeed, in the first instance, the user gave involuntarily considerable information to the actors of e-commerce. The IP addresses associated with cookies that each site may file on the consumer's computer allow to trace a route of navigation in a very precise way: sites, page depth, conversion funnel, bounce rate. Web Analytics tools began including the most well-known Google Analytics and Xiti providing daily reports on the number of connected users (unique visitors), average time consultation of the site, keywords and requests... Secondly, the emergence of social networks has fed Big Data with information gathering, information given by consumers. This social content covers a variety of topics: unveiling of private life, viral sharing content, microblogging, conversations around brands... Thus, the volume of data and the complexity of their treatment become a real obstacle to an intelligent use of Big Data. Recently, the co-founder of Google, Eric Schmidt said that the volume of information generated by today's men reached in two days what had been observed over several centuries. Each day, Facebook produced over 500 terabytes of data while Google handled more than two million searches per minute. Simon (2011) returns to the impressive numbers of Big Data: 500 exabytes for the number of data available on the Web, consumption only for the United States of 3.6 zettabytes, a trillion of videos uploaded on You Tube. Consumers have become the '*always - we consumers*', constantly, connected consumers who provide themselves a considerable number of data. These data can be processed through a technological ecosystem that starts, gradually in place: fall of costs of storage of Data, technology maturity type NFC or RFID that finally make them accessible, appearance of such dedicated trades that Data scientists, generation of the cloud etc. The data become important intangible resources. They have to grow again with step 3 of Business Intelligence: one of the connected objects and mobile applications (smartphones, tablets). The interaction man-machine, analysis of sensory data, taking into account the contexts of navigation, or even sentimental attitudinal data that are captured by so-called NLP tools (for *natural language processing*) foreshadow this 3 step which will allow the emergence of young technology companies. For example, type Hadoop software developed by Open Source as Apache communities give birth to a multitude of start-ups. Big Data can be analyzed in terms of conversations between consumers picked up on social media like Twitter (Matos and al., 2019 ; McKelvey and al., 2012; Tinati and al., 2012).

Companies like Quantcast Analytics improve conversion rates, hotels bookings or purchases of new cars. They detect the unnecessary clicks, establish Predictive analyses that predict early summer travel, consolidate the behavioural data observed on the applications. Nevertheless, a significant number of data makes it difficult to use. Many publications are pointing the finger trouble using scientifically Big Data because they are unstructured data. However, as Jackson (2013), it is a mistake to qualify such data as "big" as they are, in fact, deeply different from what we had previously. McKinsey, due to their Gigantism Big Data go beyond the capabilities of information systems analysis. The consulting firm Protiviti Inc. notes that Big Data cannot be analyzed with the traditional tools of databases management. Moreover, the monetization of data led companies to search for new techniques and methods (Lohr, 2012). In advertising, the personalization of the message becomes an essential axis of market development.

Personalization: a remedy to the confusion

Customizing advertising content is accepted by the companies. It is seen as a solution to the problem of the hieratic growth of data. 52%[4] of digital managers consider the ability to customize the content is fundamental in on-line strategies. Risks associated with a low customization of their offer on the Web are pointed to by marketing managers. They cite, including, a disappointing experience, an ineffective site built on intuition rather than on data, products and "unintelligent" services based on a truncated view of the consumer. The lack of customization can lead to a deterioration in trading results and a weariness of consumers annoyed by the irrelevance of offers from performed queries. Where a real investment in the two axes of the digital personalization:

Website customization

Personalized communications

The site customization is usually triggered the *home page*. Indeed, the home page is often the first point of contact for the brand with the consumer. It can offer adapted to the different segments identified as part of its customer relationship management. The goal is to reduce the bounce rate (people who leave the site on the first page) and reduce the conversion funnel (number of pages to download in order to buy the product). This appearance of simplicity of the mechanics hides a real technological performance. The CRM (*customer relationship management*) must be able to identify the consumer, the segment to which it belongs and the content planned for this segment in a few milliseconds. This refined data management is the specialty of companies such as Neolane or Selligent.

The personalization of communication is used to bring potential buyers on the site. This customization can be done via the e-mail (e-mail adapted presenting an offer designed for the segment to which belongs the consumer) or digital advertising through three levers: the purchase of keywords on the search engines like Google and their partner sites, the display which corresponds to the purchase of advertising space in different formats (banners, pop - up etc.), affiliation that allows brands via platforms of affiliation to relay communication. Today, all of these levers is customizable. This customization is based on:

The purchase of client files through dealers (brokers or mega data) files which can combine thousands of data and so dozens of possible segmentation criteria

Data acquisition thanks to the navigation of users. The deposit of cookies on their computers and their IP addresses allow you to have information about their location, their preferences, their courtship of sites and their products (through key words typed) research but also their exposure to such or such advertising and their attitude (simple display or click-through rate). The generalization of the Facebook Open Graph[5] mix customer data and social recommendations. An unique Web identifier (User ID or user identification) is poised to win leading to a better "tracking" of the consumer.

The analysis of navigation within the sites. With the Web Analytics tools, it is possible to analyze the average shopping basket, the navigation within the site but also what site the user came from (referral) and exact performance of carried out advertising campaigns (number Internet users arriving through advertising, number of clicks generated, average basket etc.).

Furthermore, all on-line data are supplemented by offline data and mobile data: stores loyalty cards, geotagged, interaction with a network application (card electronic, interactive kiosk, mobile, chips) RFID,...).

Retargeting, effective advertising customization

Mouncey (2012) described the various researches conducted in the field of customization. He insists on the need to provide consumers with the relevant information made possible by a better knowledge of these. Within these new models, the launch of TouchPoints 4[6] (model of media exposure) represents a real revolution made possible by Big Data. It foreshadows the new models of advertising exposure that integrates the multi-channel data. Thus, it is possible to model the exposure of consumers to the different media digital[7] and do it in a context of purchase. If the implementation of these new models is considered to be bearer of radical change, retargeting appears as customizing the most effective advertising in recent years. This customization is made possible by the use of Big Data and worried about the profession. Indeed, retargeting is seen as emblematic of a new more technological marketing that will take away a significant number of trades including some creative professions (since creation is automated) and some dedicated trades in the reflection on the brand (including strategic planners). As noted in[8] Cavazza (2013), " retargeting is to optimize the purchase of banners targeting individual users based on their shopping journey." Some already prophesying the death of strategic planning for the benefit of surgical targeting algorithms. Specifically "If a user leaves the merchant site of an advertiser, it can send a more personalized message on another site so that the user return on his[9]". This customization is designed by a recommendation algorithm. This last analysis queries, the user profile, the path to purchase in a few thousandths of seconds and uses a skeleton of banner which has customizable dynamic spaces. The most used banners are those who follow the user throughout his navigation and include the product for which he hesitated but he has not bought. Saute a surfer on the merchant site that he just left and do buy is one of the great imperatives of commercial sites. Companies like Criteo made retargeting an extremely effective way to improve the profitability of advertising digital[10]. However, if the profitability of this technique is not contested, the perception of this type of communication with the consumer is very little studied. Recent research (Mogaji, 2020 ; Perraud, 2011) analyzed the effect of digital advertising formats on intrusiveness that is perceived by the consumer. It appears that 'some formats using causes a strong perception of intrusiveness at the user. Furthermore the perceived intrusiveness negatively attitude toward advertising format, the ad and the brand. "(Perraud, 2011, p.1). However, retargeting effects have not been studied. However, retargeting is a specific format which requires dedicated studies. Retargeting is:

Increasingly used by businesses, this now on social networks like Facebook or commercial e-mail

Customizable to the extreme which can increase the impression of violation of privacy and intrusiveness but also the feeling of relevance of advertising

A format whose persuasion is based on repetition as a banner of retargeting will be seen on a period shorter or longer[11] on all the websites on which the user navigates

Design and main results of the research

Therefore, this study attempts to answer the question. Retargeting has an influence on the perceived advertising intrusiveness and more generally on the brand image and intend to return to the site? The theoretical framework mobilized concerns:

The effects of the communications personalization on consumers and more specifically ad relevance

The concept and measurement of perceived intrusiveness

Conceptual framework

Customization and ad relevance

Ad customization is increasingly studied in two directions: the customization according to the profile of the consumer (Kim and al., 2020 ; Bauer, Reichardt, Barnes and Neumann, 2005) or location (Pura, 2005). According to Tsai and al. (2020) or Chellappa and Sin (2005), individuals are willing to share personal information in exchange for perceived benefits. An assessment is done between the perceived risk to disclose his private life and the benefits. Moreover, as show Khelladi and al. (2013), the contextualization plays a key role. Customize the advertising message based on the customer profile is not enough. We must also convey this message to the most appropriate time. Finally, custom advertising (also known as behavioral targeting) increases the effectiveness of campaigns and understanding of consumers. Yan and al. (2009) show that users who click on the same type of advertising exhibit similar behavior on the Web (1). The click rate can be increased by an average of more than 670 percent thanks to the segmentation and the design of well-targeted ads (2). Advertisements designed from recent queries consumers are more effective than those based on oldest requests (3) which tends to prove that customizing triggers the impulse purchases. With respect to the relevance of the announcement, Derbaix and Pêcheux (1995) show that there is a link between commercial involvement and personal relevance. This involvement influence the motivation to deal with the announcement and the attention.

Concept and measurement of perceived intrusiveness

Intrusiveness “pertains to the extent to which commercials disrupts the flow of an editorial unit. Findings show that consumers' attitudes toward advertising are high when the quantity and the intrusiveness of clutter are low. Competitiveness of clutter has no significant impact on attitudes toward advertising. the "degree to which conveyed by media advertising interrupts the fluidity of the editorial unit" (Ha, 1996). Advertising exposure is even more important that there is a link between the ad frequency and perceived intrusiveness (Gauzente, 2004). Thus, more ad repetition is strong, the more the feeling of intrusiveness on advertising. Hérault (2010) shows that the intrusive nature of a communication may affect, in a digital context, the adoption of technology process and intend to use (continuity of use). The perceived intrusiveness can be measured using various protocols. We supported this research on the work of Li, Edwards and Lee (2002) adapted from Gauzente (2008). The scale of perceived intrusiveness contains the following labels: it's intrusive, it's intrusive, that bother me, it is a breach of my privacy. This scale used in much research (Hérault, 2010; Gauzente, 2008) present good psychometric qualities.

A research model is proposed in the following figure (figure 1). It takes into account as a central variable perceived intrusiveness. It includes two antecedent variables: ad repetition and ad relevance compared to the queries that are one of the two features of the retargeting and, more generally, the use of Big Data in digital advertising. Brand image is considered to be a variable mediator of intend to return to the site and perceived intrusiveness. We will therefore make the following hypotheses:

H1: **perceived intrusiveness can influence negatively the intention to return direct way (H1a) and indirect (H1b) via brand**. Briggs and Hollis (1997) cites by Perraud (2011) show that the format of an advertisement has an effect on the perception of brand and on attitudes and behaviors.

H2: **ad repetition has a positive influence on perceived intrusiveness**.

H 3: **ad relevance has a negative effect on perceived intrusiveness.** Perceived intrusiveness is considered, for the consumer, has a gene for his cognitive process, the fact that the advertising is relevant with this process can diminish the feeling of intrusiveness.

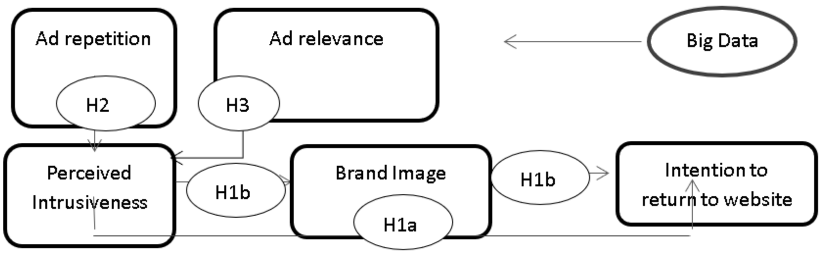

Figure 1: conceptual model

Research design and main results

We conducted two exploratory researches, a qualitative and the other quantitative. The first qualitative research was about 20 individuals (average age 36 years, 70 percent of women, 30% of men in June 2020). After exposition to a retargeted ad, we collected their impressions. This first study was preparatory to the quantitative study and had no generalized character. Nevertheless, we were able to identify some areas of reflection on the perception of digital advertising and beyond Big Data by the consumer (table 1). We also wish to clarify that the whole sample was made up of students of continuing training in marketing.

Emerging themes of the qualitative interviews	Key observations
The magic of technology	The technology that enables retargeting is misunderstood and unknown to consumers surveyed. Their knowledge of Big Data is very rough. The basics of cookies, behavioral targeting or tracking are poorly understood. The technology to the extreme customization is considered "to magic." " *How do know? How can they be so precise?* »
The concern about the use of the data	An important concern is the use of personal data. This concern focuses on social networks considered more intrusive than queries on search engines.
The image of the brand	The brand seems to suffer from retargeting. Repetition seems the most promising of a deterioration of the image of the brand. Comments such as ' *the brand can't convince, then it's harassing us* ' are frequent.
The desire to purchase the product	The urge to buy the product is ironically increased vision of personalized advertising. What is appreciated is the *cross-selling*(ability of advertising to propose a complementary offer in addition to the product)

Table 1: key findings of the exploratory study

Regarding the quantitative survey, we did an experiment on 200 Internet users. They were asked to follow on their computer, a specific navigation scenario. For men (60% of the sample), the specific query type wear on equipment of garden on the Google search engine. At the time of the survey, a commercial link from a major specialized distributor displayed. He asked users to click on the link to access the offer and follow the funnel of purchase until the time of the choice of the means of payment. The second step was to leave the merchant site and then to browse several sites who had been selected beforehand as sites practicing retargeting. Half of the sample had to navigate three site consecutively, the other half on 6 in order to get a certain variance in rehearsal. All the sites relayed the promotional ad which included a price offer for garden furniture. The same scenario was followed for the female sample with as query a fashion item. The merchant site selected was a mail that practice of systematically retargeting. At the end of this experiment, a questionnaire was submitted to all of the sample. Beforehand had been tested on another sample the scale of intrusiveness that is perceived and the scale on the extent of branding (Keller, 1993). For reasons of synthesis, we will only present the meaningful connections between variables in the model.

Significant relationships between variables	Repetition of ad - perceived intrusiveness	Ad - perceived intrusiveness relevance	Perceived intrusiveness - Image of the brand	Perceived intrusiveness - Intention to return	Image of the brand- Intention to return
[12] Student's T	17.4	-12,01	-4.13	NS	-4.7
Validation of the hypothesis	H2 validated: the repetition	H3 validated: the ad	H1b validated: the perceived	H1 has not validated:	H1 b validated:

	of the ad increases the perceived intrusiveness.	relevance diminishes the sense of perceived intrusiveness.	intrusiveness degrades brand image.	there is no link between perceived intrusiveness and intend to return.	there is a link between brand and the intention to return to the website.

Table 2: key relationships between variables in the model and validation of the hypotheses

Perceived intrusiveness affects the brand image. Brand appears as pursuing consumers in its offers without respecting their navigation. Loss of image has a direct and negative influence on the intention to return to the site. However, when brand image[13] is not taken into account by consumers, perceived intrusiveness has no influence on the intention to return. The latter does not account issuing brand in its judgment of the ad but only the promotional offer. Finally, ad repetition increases perceived intrusiveness which implies that brands media strategies must take into account very carefully the average level of repetition. As for the relevance of the ad, it plays a positive role in the perception of retargeting by the consumer[14]. Customizing an ad has a positive influence on the persuasion of the user and confirms the findings of the literature. However, it must be used within the brand positioning and with an acceptable repetition level to the consumer.

Conclusion

This research highlights the importance to the consumer of the acceptance of new targeting techniques made possible by Big Data. This acceptance can be facilitated by perceived relevance received ads (they correspond to a real service and facilitate research) and the implementation of intelligent capping systems which limit repetition.

The attitude of the consumer over the use of its private data in a commercial context raises many questions in marketing today. The European CNIL and private consumer initiatives demand better supervision of the use of such data [15]. Big Data used for advertising purposes are already over the field of competitive intelligence.

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Notes

[1] CTR Average display advertising clickthrough rates (CTRs) – 2020 compilation, https://www.smartinsights.com/internet-advertising/internet-advertising-analytics/display-advertising-clickthrough-rates/

[2] The conversion rate is defined as the percentage of visitors making a purchase on a site during a visit.

[3] Silicon Graphics was a company specializing in computer graphics, 3D, video processing and computing performance. It went bankrupt in 2009.

[4] source: Quarterly Digital Intelligence Briefing: Personalization, Trust and Return on Investment in association with Adobe.

[5] some examples of tools called social Plugin built into most e-commerce sites: buttons 'like', 'comments' space, via his Facebook connect button...

[6] for further information see: www.ipatouchpoints.co.uk

[7] the various digital media are grouped under the acronym "Poem" for P (paid media - purchase of keywords, paid digital media), O (owned media - website of the mark), E (earned media - presence on) social networks), M (media).

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[10] Criteo is the average click of a custom banner rate of 0.6%, but it can go up to 2,5% in some campaigns. Using retargeting, Amazon has 35% of its sales with this technique.

[11] the so-called retargeting cookies have a life of 30 days.

[12] the Student's t test assesses the significance of the relationship between indicators and build it. It is significant from 1.96.

[13] in this case, it is ignores the mediating character of brand image.

[14] the relevance of the announcement has a positive influence on the image of the brand (T of Student: 6.7). This link has been observed during the analysis of the results but had not been the subject of preliminary assumption.

[15] Facebook was sentenced in July 2013 to pay 20 million dollars in damages and interest to members for an advertising model hybrid using the preferences of the users to the brand promotion.