How does individual's privacy preferences affect ad attitude? The roles of psychological reactance and the degree and frequency of online personalized ads

Camille **TESSIER**
Final Year Master's Student
EM Nomandie Business School
camille.tessier23@em-normandie.fr

Romain **SOHIER**
Assistant Professor in Marketing
EM Normandie Business Shcool
rsohier@em-normandie.fr

Fidan **KURTALIQI**
Assistant Professor in Marketing
Audencia Business School
fkurtaliqi@audencia.com

Mustafeed **ZAMAN**
Assistant Professor in Marketing
EM Normandie Business Shcool
mzaman@em-normandie.fr

Abstract

The recommendation algorithms allow to generate personalized suggestions online. These recommendations are based on the collection of personal information from Internet users. However, these personalized online recommendations, which are sometimes abusive or poorly implemented, can generate psychological reactions characterized by a feeling of intrusiveness. We have collected 470 valid responses (215 for iPhone 11 and 255 for Nike shoe) and used Structural Equation Modelling SmartPLS 3.0 to evaluate the impact of recommendation algorithms on Internet users while browsing social networks, and seeks to demonstrate whether the nature, origin, relevance and frequency of recommendations affect consumers differently.

Key words:

Retargeting – Personalized Ad Attitude - Psychological Reactance - Attitude Towards Ads – Multi-group Analysis

1. Context

The recommendation algorithm allows to generate personalized online suggestions (Kim et al., 2019). These recommendations or personalized suggestions are based on the collection of personal information of the Internet users. Therefore, marketers have the possibility to display advertisements based on the Internet users' recent search behaviour, which is known as behavioural retargeting (Lambrecht and Tucker, 2013). Marketers may use content-based targeting (i.e., what consumers read) (Zhang and Katona 2012) and/or keyword-based targeting (i.e. what consumer write in search engines like Google) (Desai et al., 2014). The emergence of Big Data and Artificial Intelligence (AI) has given marketers more possibilities for personalized ads. Big Data allows marketers to use real time bidding ads (Sayedi, 2018) and AI is used for personalized ads based on the behavioural targeting, IP addresses and web-surfing history of the customer (Kumar et al., 2019). Indeed, when a consumer visits a website, he is asked to "accept the cookie policy". Upon his acceptance of the cookie, a software-like is implemented on the consumer's computer or mobile devices and it allows to collect & store information on customer's Internet search. These methods can be seen positively because consumer may discover products that they like or looking for as these methods are based on their needs or motivations. Moreover, it can also reduce the time of searching a product that consumer is looking for (Kim et al., 2019). However, if these personalized online recommendations are poorly implemented, they can generate negative emotions as psychological reactions characterized by a feeling of intrusiveness or impacts on privacy (Van Doorn and Hoekstra, 2013; Zaroula et al., 2017). Therefore, marketers must take into consideration these factors for their digital marketing strategies as they can affect the attitude of their customers towards their brands as well as their general attitude towards the brand.

Our study follows this literature stream. The aim of this paper is twofold: (1) examine the impact of recommendation algorithms on Internet users while browsing social networks, and (2) demonstrate whether the nature, origin, relevance and frequency of online personalized ads affect customers differently.

In this study, we investigate three levels of ads personalization and we study how individual privacy influences psychological reactance and finally the ad attitude. As the frequency of ads is an important variable on online advertising (Försch and de Han, 2018), we also include this variable as a moderator of psychological reactance.

2. Conceptual Framework

2.1. Importance of ads' personalization

Recommendation algorithms have been considered as a vital online advertising tool (Viera and Ribeiro, 2018). By taking into consideration the customers' internal & external browsing history and personal information, the dynamic retargeting allows firms to improve online advertising content on external/third-party websites (Lambrecht and Tucker, 2013). In other words, customers who has previously visited the company's website, will be shown ads of the products they have looked at before on company's own website. With the development of technologies, the e-commerce and digital marketing are becoming data-intensive, and companies are looking for more accurate advertising in order to improve their click-through rate (CTR) prediction and conversion ratio (CR).

Research has shown that personalization has positive effects on brand and campaign responses (Shanahan et al., 2019). The personalization is also related to the need for uniqueness (Tian et al., 2001) and has been primarly studied with one-to-one marketing and concepts of targeting, profiling (Petrison et al., 1997). The main advantages of personalization are to enhance ad credibility, to reduce customer's resistance against ads and improving brand awareness (Tran, 2017). Indeed, marketers with a personalization strategy have to learn what customers exactly need, and match their offers accordingly (Murthi and Sarkar, 2003). In addition, the personalization allows marketers to increase customer loyalty and trust. And, it allows firms to engage in a relationship with their consumers and co-create values (e.g., the case of myNutella (Wright et al., 2006). For instance, Masłowska et al. (2011) show that the use of the first name in a commercial email positively affect the respondents' evaluation of the message.

To conclude, the concept of personalization has a double advantage for marketers and consumers. Firstly, from a customer perspective, a personalized ad helps the consumer to focus on the product that they want (Bleier and Eisenbeiss, 2015a, 2015b). Secondly, from a company perspective, a targeted ad is cost saving and helps brands not to propose poor ads that may be neglected or cause resistance to the brand. So, brands should target the "good consumer" that fit with the ad.

Although the recommendation algorithms have become vital for e-commerce, poorly implemented recommendations may generate negative consequences as psychological reactance (Brehm and Brehm, 2013; Brinson et al., 2018) when consumers view a pop-up, an ad on their social network news feed, a preroll video ad relative to a previous Google search. Therefore, the risk for the brand is to develop a negative attitude toward the ad (Akestam et al., 2017).

2.2. The psychological reactance

The psychological reactance may occur when an external stimulus, for example a persuasive message that we can see on the ad, is perceived to threaten, hinder, or eliminate an individuals' freedom to choose. This concept has been used to study stereotypical ads that share a cliche and can threat people (i.e. most ads represent women very thin or like the so-called « women as objects ») (Eisend, 2010 ; Akestam et al., 2017) or with the loyalty programs (Pez, 2012). In both cases, the consumer has some choices : he does not see that we are trying to influence him, he could accept the persuasive message or he could not. In the third option, he will develop a reactance and try to restore his freedom. He could refuse, criticize and/or resist to the message by an inverse behavior : this is referred to the boomerang effect (Clee and Wicklund, 1980). On internet, the (re)targeted ads can develop reactance when consumers are using some software to avoid ads (i.e. Adblock) or do not accept cookies. Depending on individual psychologocial variables (i.e. privacy concern, privacy protection), the psychological reactance can occur and influence a feeling of intrusiveness (Van Doorn and Hoekstra, 2013), a loss of trust (Bleier and

Eisenbeiss, 2015b) a scepticism toward the ad (Zarouali et al., 2017) or an avoidance (Miltgen et al. 2019).

3. Method and Results

3.1. Method

We study the impact of individual preferences (privacy protection, privacy invasiveness and information ad value) and frequency (as a control variable) on psychological reactance (mediating variable). The second part of the model aims to test the effect of reactance on general ad attitude. We conducted a quantitative study on two products (Apple iPhone 11 and Nike Running Shoe) with for each of them three degrees of personalized online advertising; in total six surveys. The scenario (i.e. same scenario for Apple and Nike) was as follow: Step one, "*You are looking the iPhone 11 on apple website";* we showed to our samples a screenshot (i.e. a picture of the IPhone 11 on the Apple Website) and they responded to our questions. Step two, we indicated to our samples "*some days later, you have this ad on your Instagram*". The sample one saw a picture of the iPhone 11 on Instagram with the Apple logo, the sample two, with Bouygues logo (telecommunication operator retailer) and sample three, the Amazon logo (e-commerce retailer).

Table 1. Descriptive statistics of the sample

		Apple	
	Apple	Bouygues	Amazon
N	80	66	69
%	37.21%	3.70%	32.09%
		Nike	
	Nike	Decathlon	Amazon
N	87	72	96
%	34.12%	28.24%	37.65%

Table 2. Characteristics of the sample

Gender	N	%
Male	156	33.19%
Female	314	66.81%
Age	**N**	**%**
1-2	20	4.3%
3	175	37.2%
4	44	9.4%
5	145	3.9%
6-7-8	86	18.3%
Instagram*	**N**	**%**
1	144	3.6%
2	121	25.7%
3	121	25.7%
4	84	17.8%

*(preference order vs. Facebook, Twitter, Youtube)

A total number of 470 responses were collected from online survey in France (See table 1 and 2). We used SEM (Structural Equation Modelling) SmartPLS 3.0 test our hypotheses (Ringle et al., 2015 ; Vinzi et al., 2010). Reliability and validity of the constructs were evaluated using Cronbach's alpha (α), composite reliability (CR), and average variance extracted (AVE). We had α value greater than 0.70 (Hair et al., 2016; Nunnally and Bernstein, 1994), the CR exceeded .70 (Fornell and Larcker, 1981; Hair et al., 2016), and the AVE was greater than 0.50 (Bagozzi and Yi, 1988; Barclay et al., 1995; Fornell and Larcker, 1981; Hair et al., 2016). To assess the discriminant validity of the measures, we used the HTMT (Heterotrait-Monotrait Ratio) method (Henseler et al., 2015) (see Table 3). To compare the different origins of (re)targeted ads, we have ran multiple MGA (Multi-Group Analysis) (Hernandez-Perlines, 2016).

Table 3. Construct reliability and validity and heterotrait-monotrait ratio (HTMT)

	α	CR	AVE	1	2	3	4	5	6
1. Ad Attitude	.924	.923	.669						
2. Fréquence	.766	.776	.539	.324					
3. Information Add Value	.860	.859	.553	.628	.298				
4. Invasiveness	.878	.879	.709	.240	.511	.236			
5. Privacy Paradox	.817	.816	.597	.130	.279	.123	.577		
6. Reactance	.781	.785	.553	.423	.781	.344	.554	.403	

3.2. Results

3.2.1 General results

With regard to antecedents of reactance variable, our model shows significant negative effect of information ad value on reactance ($\gamma = -0.133$, $t = 11.78$, $p < 0.000$). Privacy paradox ($\gamma = 0.114$, $t = 2.91$, $p < 0.01$) and invasiveness ($\gamma = 0.173$, $t = 3.83$, $p < 0.000$) have both significant positive effect on reactance. The control variable frequency has a significant positive effect on reactance ($\gamma = 0.485$, $t = 11.78$, $p < 0.000$). Finally, reactance has a significant negative effect on ad attitude ($\beta = -0.375$, $t = 9.04$, $p < 0.000$).

Table 4. Bootstrapping results

	M	SD	*t*-Value	*p*-Value	*Sig.*
Frequency -> Reactance	.485	.041	11.78	.000	***
Information Add Value -> Reactance	-.133	.036	3.59	.000	***
Invasiveness -> Reactance	.173	.045	3.83	.000	***
Privacy Paradox -> Reactance	.114	.039	2.91	.004	**
Reactance -> Ad Attitude	-.375	.041	9.04	.000	***

Notes: M = mean. H = hypothesis, SD = standard deviation.
*Significant at .05. ** Significant at .01. *** Significant at .001.

3.2.2 MGA results

The first part of our MGA analysis consists in testing the differences for Apple scenario. In the table 5, we highlighted four differences between Apple and Amazon. Frequency and privacy paradox variable present greater positive effects on reactance with the ad displayed by Apple. Information ad value negative effect on reactance is greater with the ad displayed by Amazon. A greater positive effect of invasiveness on reactance is observed for Amazon ad display. In the Bouygues *versus* Amazon comparison, we observed four differences; in favor of Amazon, a greater negative effect of information ad value on reactance and a greater positive effect of invasiveness on reactance; in favor of Bouygues, a greater positive effect of both frequency and privacy paradox variables on reactance. We observed no differences between Amazon and Bouygues.

For Nike brand, we found only two differences in Nike *versus* Amazon and Decathlon *versus* Amazon scenarios. First, Reactance has a greater negative effect on ad attitude for Nike display. Second, reactance has a greater negative effect for the display of the ad by Decathlon.

Table 5. MGA results differences

Path differences significance	A* vs. B	A vs. Am	*B vs. Am*	*N vs. D*	*N vs. Am*	*D vs. Am*
Frequency -> Reactance	No	Yes	Yes	No	No	No
Information Add Value -> Reactance	No	Yes	Yes	No	No	No
Invasiveness -> Reactance	No	Yes	Yes	No	No	No
Privacy Paradox -> Reactance	No	Yes	Yes	No	No	No
Reactance -> Ad Attitude	No	No	No	No	Yes	Yes

*A. Apple, B. Bouygues, Am. Amazon, N. Nike, D. Decathlon,

4. Conclusion

Our general results have shown the importance of information ad value variable on reactance. Indeed, an informative ad could significantly decrease the reactance effect. However, our results highlight the positive effects of privacy paradox and invasiveness on reactance. These two variables could significantly affect the consumer behavior in rejecting the ad. Moreover, the model show that reactance can, at the end affects negatively ad attitude.

The MGA analysis allowed understanding how the type of product could moderate the links between the variables. For example, we observed more differences in the Apple scenario. An Apple cell phone is much more expensive than a Nike shoe. Therefore, the value of the product moderates the links. In addition, our results show that the retailer displaying the brand is also important. We have observed that when an ad is displayed by a retailer who is not the main sales expert for the type of product, it moderates the links in our model considerably. In addition, the results show that the informational value of the ad is better perceived when it is displayed by a non-expert. This is why the variable of the value of the advertising information in the case of Apple has no effect on reactance.

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