“A dark side of retargeting? How advertisements that follow users affect post-purchase consumer behavior: Evidence from the tourism industry in Saudi Arabia”

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A DARK SIDE OF RETARGETING? HOW ADVERTISEMENTS THAT FOLLOW USERS AFFECT POST-PURCHASE CONSUMER BEHAVIOR: EVIDENCE FROM THE TOURISM INDUSTRY IN SAUDI ARABIA

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Abstract

This study aims to explore the complex effects of post-purchase retargeting ads on consumer behavior, with a focus on expectation confirmation, satisfaction, and repurchase intentions. Additionally, it examines the influence of time spent online on these effects. Anchored in expectation confirmation theory (ECT), the study analyzes responses from 396 Saudi Arabian e-tourism customers who encountered competitive retargeting ads after purchasing an e-tourism package. The analysis employs partial least squares structural equation modeling (PLS-SEM) and multigroup analysis (MGA) to test the hypotheses. A notable finding is the direct negative impact of retargeting ads on expectation confirmation: increased exposure to such ads post-purchase seems to diminish the perception that initial expectations of the product or service are being met. The negative effect of these ads also indirectly influences satisfaction and repurchase intentions. Furthermore, the MGA results indicate variations in this negative impact based on the time spent online. Specifically, the more time consumers spend online, the stronger the negative impact, leading to a significant decrease in satisfaction and repurchase intentions. These insights reveal the complex nature of post-purchase retargeting ads and underscore the importance of accounting for consumers' online behavior. They offer valuable direction for marketers to refine retargeting strategies to better resonate with consumer expectations.

Keywords retargeting ads, consumer behavior, e-tourism, expectation confirmation, advertising, multigroup analysis

JEL Classification M31, M37, Z33, L83

INTRODUCTION

In today's digitized world, retargeting has become a crucial digital marketing tool. Businesses aim to enhance sales and engage more effectively with their audiences by creating messages tailored to users' past online behaviors. Yet, this modern technique comes with its intricacies. With its significant reliance on e-platforms for bookings and the transient nature of its offerings, the tourism industry presents unique challenges and opportunities for retargeting.

The well-documented efficacy of retargeting in driving initial purchases starkly contrasts with the relatively unexplored post-purchase realm. After finalizing a purchase, consumers frequently encounter similar adverts, potentially influencing their satisfaction with their decision. This ongoing exposure can reshape their perception of the

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initial provider and influence their likelihood to repurchase or recommend the service to others. This scenario suggests a potential dark side to retargeting, which might not only affect consumer satisfaction but also long-term brand loyalty and trust.

Using the e-tourism industry in Saudi Arabia as a backdrop, this study delves into this critical area of post-purchase retargeting. With Saudi Arabia emphasizing tourism as a significant component of its broader future vision, grasping the nuances of digital strategies like retargeting becomes paramount.

1. LITERATURE REVIEW AND HYPOTHESES

Dynamic retargeting targets past website visitors using customized adverts, reflecting products or services they have previously viewed online. This digital marketing strategy has become prevalent because it is technologically easy to implement, reaches a vast target audience in real time, and allows marketers to identify consumer interests and match their needs with available products. Lambrecht and Tucker (2013) outline a retargeting system based on three main entities: retargeters, advertisers, and consumers. Retargeters aggregate advertising space across social sites like Facebook, LinkedIn, WordPress, and YouTube, connecting advertisers to consumers. This advertising space is then sold to advertisers who wish to promote their products by showing adverts to consumers. The effectiveness of this strategy has attracted much attention from researchers in terms of the importance of advert personalization, positive and negative effects, timing and frequency, advertising exposure, and variations of retargeting ad effects across different stages of the consumer journey.

Building upon the effectiveness of this strategy, Sahni et al. (2019) identified positive effects of retargeting, discovering that retargeting leads to a 14.6% increase in users revisiting a website within the first four weeks of targeting, with a 33% efficiency rate in the first week. Their study found complementarity in retargeting, where users exposed to advertising in the first week were significantly influenced by retargeting in the second week, indicating a positive effect on purchasing decisions. Notably, the study did not show decreased retargeting effectiveness with increased exposure.

Shifting to economic dimensions, Chen and Stallaert (2014) examined the economic impacts of behavioral targeting in online marketing. A horizontal differentiation model was used to analyze the user-ad alignment. They found that behavioral targeting can notably increase revenue for online publishers, sometimes even doubling it. However, outcomes depend on advertiser competition and valuations. The study identified two main effects, the competitive and propensity effects, which determine the revenue outcomes. Importantly, while behavioral targeting can elevate overall welfare and assist smaller advertisers, large advertisers might see fewer benefits and hesitate to shift away from conventional advertising.

Several studies have examined the dual-edged nature of retargeting. For instance, Kim and Ohk (2017) involved 258 participants to assess the contrasting effects of retargeting. Their findings indicate that when executed effectively, retargeting can elicit positive emotions in potential customers, thereby exerting a favorable impact. However, if the quality of retargeting is low, it can have adverse consequences, affecting the company's brand reputation and causing unfavorable emotional responses in customers. A similar phenomenon occurs with excessive banner ad displays, as overuse of retargeting can induce feelings of pressure and erode trust in potential customers.

Zarouali et al. (2017) delved into how advertising on Facebook affects adolescents' skepticism and purchase intentions. The article found that retargeting ads generally increase purchase intentions. However, when adolescents receive information about the advertising technique or have high privacy concerns, their skepticism increases, leading to lower purchase intentions. These findings have implications for policymakers, practitioners, and educators.

On a related note, Farman et al. (2020) explored consumer reactions to retargeting ads, sometimes deemed "creepy." The study with 280 participants revealed that behavioral targeting boosted purchase intent directly, but also had indirect negative implications. Specifically, it led to heightened perceptions of marketing surveillance, increasing feelings of threat, psychological reactance, negative ad views, and reduced purchase intent. The indirect cost of this perceived surveillance was quantified at a 4.5% reduction in purchase intent.

Navigating the fine line between personalization and privacy, Van Doorn and Hoekstra (2013) focused on the balance between personalizing ads for consumers and the privacy implications. Results show that high levels of personalization can make consumers feel intrusive and decrease their purchase intentions. Discounts only partially counteract this effect. However, when ads closely align with consumers' needs, they can partially alleviate intrusiveness, but excessive personalization can still reduce purchase intentions.

Further to the interplay between levels of personalization and privacy concerns, Aguirre et al. (2015) delve into the impact of various methods for gathering data on the success of online advertising tailored to the individual, shedding light on the personalization paradox. It finds that transparent data collection enhances personalization success, while covert methods reduce effectiveness due to heightened consumer vulnerability. In a similar context, Bleier and Eisenbeiss (2015) found that for less trusted retailers, high-depth personalization leads to increased reactance and privacy concerns, negatively affecting click-through intentions.

Emphasizing the importance of privacy in retargeting ads, a survey by Cooper et al. (2023) included 818 US internet users and revealed that 26% like relevant ads and accept some tracking methods, 25% are neutral, 34% prefer relevant ads but are cautious about data collection, and 15% oppose the methods entirely. These findings shed light on diverse perspectives concerning retargeting ads and their privacy implications.

Acknowledging the significance of timing in retargeting ads, Li et al. (2021) examined how the timing of e-commerce retargeting ads impacts consumer behavior. For instance, it uncovers that displaying ads too early can diminish consumers' purchase intentions. Their analysis, involving over 40,500 customers, indicates that early retargeting (30 to 60 minutes following shopping cart abandonment) reduces purchase likelihood. In contrast, late retargeting (between one and three days later) influences purchases in a positive manner. These insights provide a valuable understanding of how consumers respond to these ads.

Building on user behaviors, Jiang et al. (2021) analyzed the correlation between research intensity and the effects of retargeting ads using a dataset obtained from Taobao.com, the largest Chinese e-commerce platform, comprising behaviors of 104,189 consumers. Their results uncover significant findings regarding retargeting strategies. Notably, users displaying higher search intensity exhibited considerably higher conversion rates from retargeting advertisements. This insight sheds light on the effectiveness of retargeting efforts based on user search behaviors on online retail platforms.

Recent research took a turn toward the effect of retargeting ads in various stages of the consumer journey. Semerádová and Weinlich (2023) found that the performance of retargeting ads varies significantly at different customer journey stages. Their study, spanning one month in 2021 and repeated in 2022, analyzed 432 retargeting ads from a Czech online retailer. It revealed that standard retargeting is effective for utilitarian browsing, while dynamic retargeting is superior on social networks. Additionally, their analysis emphasizes that retargeting ads serve unique purposes at different consumer journey stages.

Building on the post-purchase stages, Villas-Boas and Yao (2021) investigated the optimal retargeting strategy for firms. When consumers search for product information, researchers highlighted the limited control firms have over retargeting ads. They pointed out that consumers might continue to receive these ads even after completing a purchase, which could affect the post-purchase impact of retargeting ads.

The existing research has acknowledged the gap in understanding the post-purchase effects of retargeting ads. Johnson et al. (2017) stated that if retargeting ads lead to reactance in consumers, it can undermine the effectiveness of advertising. Therefore, as discussed by Baek and Morimoto (2012), it is essential to acknowledge that the in-

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fluence of these ads goes beyond their role in driving initial purchases. They also have the power to shape consumers' post-purchase behavior, impacting their satisfaction levels and shaping their intentions for future purchases.

This study focuses on the negative effects of retargeting on the post-purchase stage of the buying process. To study this effect, retargeting is framed within the expectation confirmation theory (ECT), as this makes it possible to link retargeting with expectation confirmation, satisfaction, and repurchase intentions. ECT was created to clarify how satisfaction is influenced by expectations, perceived experiences, and the disconfirmation of those expectations (Oliver, 1977, 1980). ECT compares consumer notions regarding a service or product before purchase (expectation) with their post-purchase opinion of the product (experience). It, therefore, measures whether expectations are met.

The association between expectation confirmation, satisfaction, and repurchase intentions is well-documented in existing research and has also been tested in several contexts, including e-tourism. Zhong et al. (2015) aimed to understand Chinese user behavior regarding mobile travel booking services utilizing the expectation confirmation theory. They found that expectation confirmation is a significant driver of satisfaction, and users' intention to continue using mobile travel booking services primarily hinges on how satisfied consumers are.

The type of retargeting ads, whether for less or more competitive offers than the initial purchase, is assumed to influence the consumer's expectation confirmation and satisfaction by altering the reference point. Consumer satisfaction after purchasing an offer (A) depends on the quality of the post-purchase competitive offer (B) and the offer (C). Offers by competitive websites using retargeting ads may be better or worse than the purchase (offer A). However, this study only considers the case where the post-purchase retargeting offer is considered more competitive than the original purchase from the respondent's perspective. Competitive retargeting ads are assumed to modify a consumer's original expectations (Pinquart et al., 2021) and are also assumed to indirectly affect satisfaction and repurchase intentions.

Chen and Lin (2019) examined the impacts of online advertising on user satisfaction and future buying behavior through social media. The article delved into the role of e-word of mouth – a notable form of social media marketing – and its influence on user intentions such as continued usage, participation, and purchases. Through a survey of 502 social media users, they identified that social identification and perceived value are significant mediators. These factors not only impact user satisfaction directly but also shape their broader intentions on social media platforms.

To understand the correlation between using digital platforms and making online purchases, Zhang et al. (2017) analyzed data from 7,402 unique users, monitoring their internet-based searching and buying actions throughout the year, encompassing 140,291 distinct purchase transactions. The findings show a positive correlation between increased social network usage and online shopping activity. Advertising exposure is related to the time a consumer spends viewing media. It has been found that greater exposure to advertising, including on social media platforms, is associated with better advert content recall and a higher purchase probability. The more time consumers spend online, the more likely they will encounter relevant information or better promotional offers. The link between advertising efficacy and online time is closely related to consumer information processing. Thus, the daily time spent online was included as a factor that can moderate the effect of retargeting ads.

Existing research has extensively explored the influence of retargeting in digital marketing, but a clear gap remains regarding its post-purchase implications. Building on this foundation, this study aims to assess the influence of retargeting ads following a purchase on the confirmation of expectations, satisfaction, and repurchase intentions among Saudi Arabian e-tourism users. The potential influence of advertising exposure on retargeting effects is also evaluated. The subsequent hypotheses have been developed in light of the preceding literature review:

H1: Expectation confirmation has a positive association with satisfaction.

H2: Satisfaction has a positive association with repurchase intentions.

H3: Retargeting is negatively related to expectation confirmation.

H4: Retargeting is negatively and indirectly related to satisfaction and repurchase intentions.

H5: The daily time spent online by users has a significant impact on their perception of retargeting ads, leading to differences in expectation confirmation, satisfaction, and repurchase intentions.

2. METHODOLOGY

The sample consisted of e-tourism consumers in Saudi Arabia. Each participant purchased an online tourism service and was exposed to more competitive post-purchase retargeting ads. Participants were administered a questionnaire with measurement items regarding the four constructs: expectation confirmation, satisfaction, repurchase intentions, and retargeting. The survey was drafted in English and then translated into Arabic using the back-translation procedure (Brislin, 1976). A form's hyperlink was distributed through social media, and individuals willing to participate in the survey provided their email addresses. Subsequently, an automated email containing the survey link was dispatched to those respondents. 850 emails were sent; 396 valid responses were collected after removing incomplete questionnaires, yielding a 46.5% response rate. This rigorous approach ensured data collection efficiency and minimized potential biases, providing a comprehensive dataset for analysis.

The questionnaire responses were scored according to a 7-point Likert scale from 1 ("strongly disagree") to 7 ("strongly agree"). Table 1 provides the definitions, list of items, and references for each construct in this study. Scales introduced by Bhattacherjee (2001) were used to measure expectation confirmation, satisfaction, and repurchase intentions. A scale based on Dubrovski's (2001) consumer buying-decision model was created to assess the impact of retargeting.

Table 1. Construct definitions and measurements

Construct	Definition	Measurement	Source
Expectations (EC)	The degree to which perceptions match (confirmation) or differ from (disconfirmation) expectations.	EC1. The online service of the e-tourism website meets my expectations. EC2. The e-tourism website provides me with all the essential info to decide. EC3. The sales service and payment process provided by the e-tourism website meet my expectations.	Bhattacherjee (2001), Oliver (1980)
Satisfaction (ST)	The degree of contentment and happiness that consumers derive from their purchase.	ST1. I am satisfied by the choice to utilize the service from the e-tourism website. ST2. I made a wise decision by choosing the service from the e-tourism website. ST3. I am happy with my previous choice to utilize the service from the e-tourism website. ST4. Using the services provided by the e-tourism website was the right thing to do.	Bhattacherjee (2001), Oliver (1980)
Repurchase intentions (RI)	An assessment of the probability that a customer will conduct another transaction through the e-tourism website or app.	RI1. I want to continue purchasing from the e-tourism website rather than discontinuing it. IRI2. I intend to continue using the service of the e-tourism website I used rather than use another e-tourism website.	Bhattacherjee (2001)
Retargeting (RE)	An evaluation of how competitive the post-purchase retargeting ads were in relation to the consumers' actual purchase.	RE1. The retargeted advert offer was better in terms of value than the offer I purchased. RE2. The retargeted advert offer was cheaper than the offer I purchased. RE3. The retargeted advert offer was better regarding features than the offer I purchased. RE4. The reputation of the e-tourism website showing the retargeted advert was better than that of the e-tourism website I purchased from.	Dubrovski (2001)

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Time spent online was classified into three categories: <1 hour, 1-5 hours, and >5 hours (12.87%, 65.65%, and 21.46% of the participants, respectively). This categorization was used as various studies have found that most internet users are online for an average of 1 to 5 hours daily (Mutalik et al., 2018; Fettahlıoglu et al., 2019; Moralista & Oducado, 2020), including in Saudi Arabia (Al-Zahrani, 2015).

In terms of statistical methods, this study employed partial least squares structural equation modeling (PLS-SEM) to estimate the model. This multivariate technique enables analysis of a multi-block of manifest variables forming latent variables when a system of linear relationships is hypothesized to exist between the blocks (Vinzi et al., 2010). PLS-SEM estimates the causal relationships between latent variables that maximize the explained variances between blocks (Hair et al., 2021). This method has several advantages: it provides robust estimates when working with small sample sizes, is free from the distribution hypothesis (Hair et al., 2019), and is especially indicated when the research approach is exploratory and prediction-driven. PLS-SEM includes two model estimates: an outer model analyzing the connection between latent variables and manifest variables and an inner model that examines the causal relationship between latent variables.

Using an iterative algorithm, latent variables are estimated using manifest variables according to the nature of the relationship, following a reflective or a formative scheme (outer model). A reflective scheme is used when the latent variable causes the set of manifest variables, which are highly correlated. In contrast, a formative scheme is used if manifest variables cause the latent variable. Finally, the path coefficients (inner model) that reflect the strength of the causal relationships between latent variables are estimated using multiple or simple linear regression. For technical details of the method and the validation criteria used for the outer and inner models, see Vinzi et al. (2010), Hair et al. (2019), and Do Valle and Assaker (2016).

To test the effect of time spent online on the model's coefficients, multigroup analysis (MGA) was used, a standard way to analyze the effect of a categorical variable when using PLS-SEM (Hair et al., 2017). Different models are estimated, one for each level of a categorical variable, and the model coefficients are then compared using a statistical test to check for significant differences. In this case, three models were estimated reflecting time spent online (<1 hour, 1-5 hours, and > 5 hours). Among the several available tests (Hair et al., 2017), the multigroup analysis PLS-MGA proposed by Henseler et al. (2009) was employed. Smart PLS3 (Ringle et al., 2014) was used to estimate PLS-SEM and to perform PLS-MGA.

3. RESULTS

Since all constructs were reflective, following Hair et al. (2019) and Do Valle and Assaker (2016), latent variables were validated by calculating classical quality indices: Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). Loadings' strength and significance were also checked using 5000 bootstrapping resamples (Hair et al., 2019; Latan & Noonan, 2017) (Table 2). Both Cronbach's alpha and composite reliability exceeded the minimum threshold of 0.7, AVE exceeded the minimum threshold of 0.5 in all cases, and all loadings surpassed the suggested value of 0.7 (Hair et al., 2019) and were significant according to the bootstrap intervals. Also, discriminant validity was assessed by the heterotrait-monotrait (HTMT) ratio, as proposed by Franke and Sarstedt (2019) (Table 3), resulting in values lower than the conservative threshold of 0.85 in all cases. Furthermore, common method bias (CMB) was checked using the full collinearity test approach (Kock, 2015). The results are presented in Table 4. Since the variance inflation factor (VIF) was below the 3.3 threshold for all latent variables, according to Kock (2015), CMB could be ruled out.

Results of the inner model are detailed in Figure 1 and Table 5 (path coefficients, significance, and model goodness-of-fit) and Table 6 (model predictive power). Expectations confirmation had a positive impact on satisfaction (b = .666), and satisfaction had a positive impact on repurchase intentions (b = .670). As expected, retargeting had a negative impact on expectation confirmation (b = –.324). All coefficients were significant according to the confidence intervals, supporting H1-H3. Support for H4 was also found since retargeting al-

Table 2. Reliability and validity criteria

Construct/indicators	Factor loadings	2.50%	97.50%	Alpha	CR	AVE
Expectations (EC)				0.845	0.906	0.763
EC1	0.870	0.830	0.903			
EC2	0.885	0.847	0.915			
EC3	0.866	0.816	0.900			
Satisfaction (ST)				0.722	0.877	0.781
ST1	0.873	0.838	0.902			
ST2	0.887	0.849	0.919			
ST3	0.889	0.847	0.921			
ST4	0.848	0.790	0.893			
Repurchase intentions (RI)				0.868	0.910	0.716
RI1	0.904	0.875	0.927			
RI2	0.863	0.817	0.899			
Retargeting (RE)				0.897	0.929	0.765
RE1	0.829	0.768	0.873			
RE2	0.883	0.850	0.911			
RE3	0.859	0.809	0.895			
RE4	0.812	0.759	0.856			

Table 3. HTMT ratios

HTMT Ratio	Value	2.50%	97.50%
Repurchase intentions → expectations	0.720	0.601	0.829
Retargeting → expectations	0.375	0.223	0.513
Retargeting → repurchase intentions	0.206	0.070	0.371
Satisfaction → expectations	0.764	0.679	0.836
Satisfaction → repurchase intentions	0.827	0.741	0.908
Satisfaction → retargeting	0.273	0.143	0.407

Table 4. Evaluation of common method bias

	Expectations	Repurchase intentions	Retargeting	Satisfaction
VIF	1.004	1.010	1.045	1.054

so had significant indirect effects on both satisfaction (b = –.216) and repurchase intentions (b = –.145) (Table 5).

The standardized root mean squared residual (SRMR) at .054 fell below the 0.08 threshold limit (Hair et al., 2017), indicating that the model's goodness was adequate. Concerning the model's predictive power (Table 6), for repurchase intentions and satisfaction, R^2 was equal to .449 and .443, respectively, and Q^2 was equal to .343 and .336, respectively. Those values, according to Hair et al. (2019), point to moderate predictive power, as did the PLSpredict procedure (Shmueli et al., 2019) where, according to the root mean squared error (RMSE), the PLS model produced a lower prediction error than the naïve LM benchmark for at least 50% of the constructs.

Table 5. Path coefficients, bootstrap confidence intervals, and standardized root mean square residuals

Effect	H	Path coefficient	β	2.50%	97.50%	Significant
Direct	H1	Expectations on satisfaction	0.666	0.589	0.737	yes
	H2	Satisfaction on repurchase intentions	0.670	0.593	0.740	yes
	H3	Retargeting on expectations	–0.324	–0.447	–0.201	yes
Indirect	H4	Retargeting on satisfaction	–0.216	–0.296	–0.139	yes
	H4	Retargeting on repurchase intentions	–0.145	–0.201	–0.092	yes
SMSR = 0.054						

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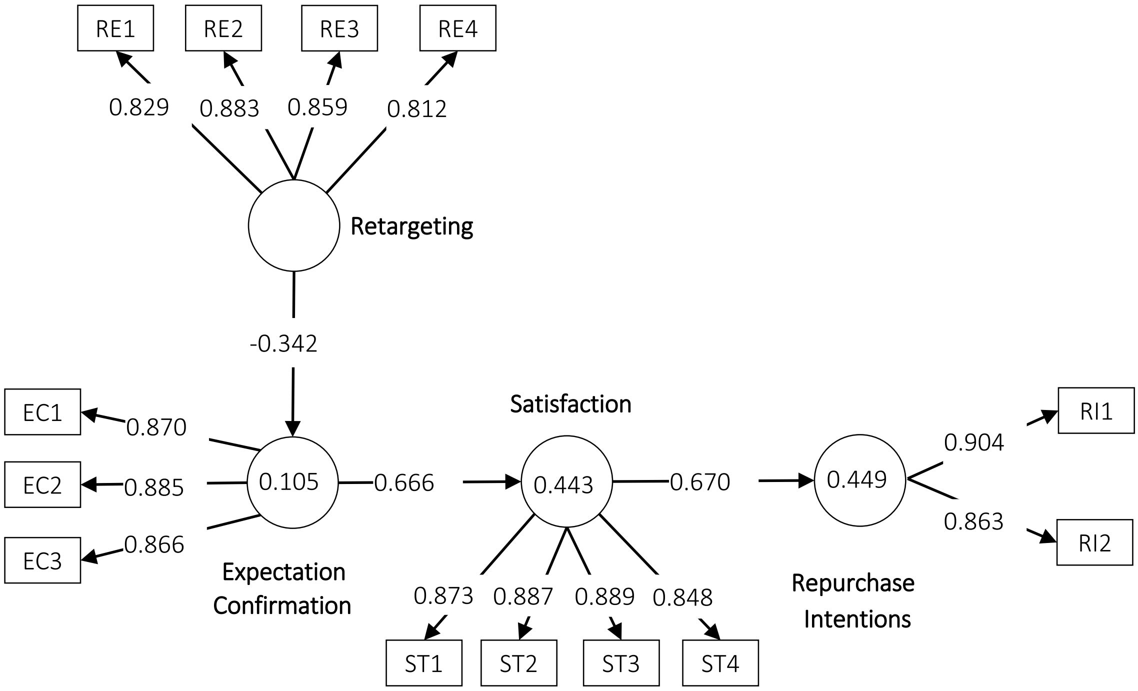

Figure 1. Path diagram results

Before running the MGA for the online time groups (<1 hour, 1-5 hours, and >5 hours), the measurement invariance of composite models (MICOM) procedure (Hair et al., 2017) was applied to check measurement invariance. This process comprised three consistent stages: (1) establishing configural invariance, (2) ensuring compositional invariance, and (3) confirming the equality of composite mean and variance values. According to Hair et al. (2017), steps 1 and 2 are prerequisites for running the MGA.

Configural invariance was secured by explicitly defining each latent variable – namely retargeting, expectations confirmation, satisfaction, and repurchase intentions – consistently across all three online time groups in the PLS-SEM. Compositional invariance was then established by comparing the correlations of latent scores between groups to a reference distribution of correlations generated through permutation of the groups. Acceptance of the null hypothesis of a theoretical correlation of 1, indicating composite invariance of the construct, occurs if the observed correlation is within the upper 95% of the distribution. Subsequently, to assure complete measurement invariance, tests were conducted to compare mean values and variances of latent scores across groups against the reference distribution obtained by permutation of the groups.

Table 6. R^2, Q^2, and PLS predict procedure

Construct	PLS RMSE	LM RMSE	Differences
EC1	1.015	1.021	–0.006
EC2	1.151	1.155	–0.004
EC3	1.189	1.185	0.004
RI1	1.285	1.294	–0.009
RI2	1.318	1.329	–0.011
ST1	1.141	1.142	–0.001
ST2	1.127	1.137	–0.01
ST3	1.186	1.192	–0.006
ST4	1.227	1.222	0.005
Repurchase intentions R^2 = .449; Q^2 = .343. Satisfaction R^2 = .443; Q^2 = .336.			

Note: EC = expectations confirmation; RI = repurchase intentions; ST = satisfaction.

Table 7. Steps 2 and 3 of the MICOM procedure

Construct	Groups	Compositional invariance		Equality of composite values			
				Mean values		Variance values	
		Score Corr	5.00%	Mean Diff	2.5-97.5%	Variance Diff	2.5-97.5%
Expectations	<5 hr vs 1-5 hr	1 *	0.995	0.325	[–0.322–0.309]*	–0.518	[–0.628-0.529]*
Repurchase intentions		0.999*	0.989	0.234	[–0.306–0298]*	–0.112	[–0.540-0.403]*
Retargeting		0.864*	0.635	–0.070	[–0.278–0.298]*	–0.015	[–0.589-0.437]*
Satisfaction		0.999*	0.998	0.161	[–0.313–0.300]*	–0.311	[–0.541-0.422]*
Expectations	<5 hr vs>5 hr	0.999*	0.991	–0.289	[–0.347–0.339]	–0.260	[–0.637-0.537]*
Repurchase intentions		1*	0.993	–0.239	[–0.356–0.341]	0.234	[–0.494-0.480]*
Retargeting		0.855	0.984	0.708	[–0.353–0.340]	0.071	[–0.721-0.625]*
Satisfaction		0.997*	0.995	–0.313	[–0.344–0.341]	0.079	[–0.679-0.655]*
Expectations	1-5 hr vs>5 hr	0.999*	0.997	–0.565	[–0.242–0.250]	0.258	[–0.434-0.504]*
Repurchase intentions		0.999*	0.993	–0.458	[–0.243–0.252]*	0.335	[–0.364-0.387]*
Retargeting		0.997*	0.987	0.746	[–0.239–0.245]	0.100	[–0.377-0.452]*
Satisfaction		1*	0.999	–0.436	[–0.245–0.243]	0.396	[–0.379-0.395]*

Note: *Confirmed.

The results of the MICOM procedure are displayed in Table 7, indicating that step 2 was verified in all but one instance, while step 3 was only partially supported. Consequently, while configural and compositional invariance were assumed, full invariance was rejected.

MGA results for the three online time groups are reported in Table 8. The impact of retargeting ads on expectations confirmation was significantly greater for the >5 hours group than for the 1-5 hours group (p = .002). Also, the direct impact of retargeting ads on expectations confirmation for the <1 hour group was insignificant, unlike the other groups. Another indirect effect was that the retargeting effect on satisfaction and repurchase intentions increased and became significant for the >5 hours group (b = –0.318 and b = –0.222, respectively) and the 1-5 hours group (b = –0.154 and b = –0.099, respectively), but not for the <1 hour group (b = –0.184 and b = –0.135, respectively). As such, H5 was supported.

4. DISCUSSION

Digital marketing strategies aim to influence buying behavior in a particular direction (Omar & Atteya, 2020). The literature indicates that digital marketing, including dynamic retargeting (Lambrecht & Tucker, 2013; Sahni et al., 2019; Villas-Boas & Yao, 2021), can affect pre-purchase (from need awareness to purchase decision) but also post-purchase steps (satisfaction and repurchase), given that the goal is to have the consumer purchase and repurchase a particular product or service. This study, framed in ECT, investigated the retargeting effect for e-tourism in the post-purchase period, as tourists are susceptible to this effect.

Concerning the extent to which post-purchase retargeting ads influence consumer expectation confirmation, satisfaction, and repurchase intentions, findings indicate that more competitive retargeting ads negatively affect consumer expectation confirmation and indirectly affect their satis-

Table 8. Multigroup comparison results

Paths		<1 hr G1	1-5 hr G2	>5 hr G3	PLS-MGA test		
					G1 vs G2	G1 vs G3	G2 vs G3
					p-value		
Direct effect	Retargeting on expectations	–0.247NS	–0.231	–0.565	0.658	0.105	0.002*
	Expectations on satisfaction	0.742	0.666	0.564	0.196	0.075	0.165
	Satisfaction on repurchase intentions	0.732	0.642	0.697	0.157	0.352	0.755
Indirect effect	Retargeting → satisfaction	–0.184NS	–0.154	–0.318			
	Retargeting → repurchase	–0.135NS	–0.0985	–0.222			

Note: Significance ***p < .001, non-significant. Italics indicates significance at p < .05.

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faction and repurchase intentions, providing support to H3 and H4. In support of H1 and H2, as anticipated, expectation confirmation has a positive impact on satisfaction, and the latter has a positive impact on repurchase intentions, providing evidence in favor of ECT predictions (Oliver, 1981) and supported by Bhattacherjee (2001) and Zhong et al. (2015). While prior research found evidence that pre-purchase retargeting plays a vital role in either increasing (Lambrecht & Tucker, 2013; Van Doorn & Hoekstra, 2013) or decreasing (Li et al., 2021) purchase intentions, this study suggests that post-purchase retargeting may have a negative effect. In particular, the scenario in which users consider post-purchase retargeting ads as more competitive than their initial purchase was analyzed. In this case, retargeting negatively affects consumer expectation confirmation, satisfaction, and repurchase intentions.

Regarding the extent to which the relationship between post-purchase retargeting ads, consumer expectation confirmation, and satisfaction varies according to the time spent online, findings indicate that the time spent online by consumers counts. It was found that the negative effect of retargeting increases the more time the consumer spends online. Interestingly, the indirect effect of retargeting on satisfaction and repurchase intentions is not significant for consumers who spend <1 hour online. Those results support H5 and are corroborated by other research on the importance of internet surfing time (Zhang et al., 2017). Consumers who spend more time online tend to encounter a larger volume of retargeting ads. This increased exposure can strongly influence their decision-making process and online behavior. Additionally, these users are more likely to seek additional information about sellers and products. This behavior further strengthens the effectiveness of retargeting ads, as discovered by Jiang et al. (2021).

Findings suggest a crucial message for firms concerning their differentiation strategy: while differentiation is important, comparative advantage is even more critical. Thus, retargeting focusing on differentiation based mainly on competitive pricing may erode expectation confirmation, satisfaction, and repurchase intentions and induce the consumer to switch to another firm, i.e., the consumer's loyalty is undermined, and a process of mutual cannibalization is launched between firms. However, retargeting focused on differentiation based on product or service benefits may lead consumers to self-assign themselves to the right competitive offer. In this case, consumer satisfaction is less likely to be affected by retargeting ads, which, even if they offer better prices, may not provide the benefits sought by a particular segment of consumers. Future studies could examine the roles of digital skills and customer degree of involvement on the influence of retargeting ads. Time spent online could serve as a proxy for digital skills and might explain variable retargeting effects. At the same time, differences between consumer groups could be explored through consumer involvement in terms of time spent seeking products and services online. Finally, future research may also analyze the effect of retargeting on consumers when offers are differentiated by price compared to when offers are distinguished by the value delivered to specific consumer segments.

CONCLUSION

The purpose of this study was to assess the effect of competitive retargeting ads on consumer post-purchase behavior in the e-tourism sector, especially in the context of expectation confirmation, satisfaction, and repurchase intentions, framed within the expectation confirmation theory. Findings derived using PLS-SEM indicated a distinct negative effect of retargeting on these parameters. Additionally, MGA results showed this adverse impact of retargeting grew more pronounced as consumers spent more time online. Alongside the negative impact of retargeting, there was a positive effect of expectation confirmation on consumer satisfaction, and likewise, a positive effect of satisfaction on repurchase intentions was observed.

From the thorough analysis of these results, a compelling and clear conclusion emerges. It is imperative for businesses to reconsider and pivot their retargeting strategies effectively. Instead of primarily focusing on and competing based on price, there is a significant need to shift the emphasis towards highlighting the overarching value that is delivered to consumers. This strategic change enables consumers to align more organically and intuitively with brands, based on their personal preferences and the perceived value. Such an approach fosters a deeper, more authentic, and loyal relationship between consumers and brands in the dynamic digital marketplace. This realignment not only benefits consumers by providing them with choices that resonate more closely with their needs and values, but it also aids businesses in establishing a more sustainable and meaningful connection with their customer base.

AUTHOR CONTRIBUTIONS

Conceptualization: Haitham Alghanayem, Giuseppe Lamberti, Jordi López-Sintas.
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