MARKETING RESEARCH INNOVATION

IJMRI VOL 7 NO 1 (2022) P-ISSN 2576-4101 E-ISSN 2576-4098

Available online at https://www.cribfb.com
Journal homepage: https://www.cribfb.com/journal/index.php/ijmri
Published by CRIBFB, USA

BEHAVIOURAL TARGETING, PERCEPTION OF INTERNET USERS AND CLICK-THROUGH INTENTIONS: IMPLICATIONS FOR DIGITAL ENTREPRENEURS IN NIGERIA

Seun Oladele [(a)] *Oluwatimileyin Adigun* [(b)1] *Laosebikan S. Johnson* [(c)] *Femi Oladele* [(d)] *John Ajani* [(e)]

[(a)] *Doctoral Student, Business Administration Programme, Bowen University, Iwo, Osun State, Nigeria; E-mail: seun.oladele2015@gmail.com*
[(b)] *Doctoral Student, Business Administration Programme, Bowen University, Iwo, Osun State, Nigeria; E-mail: oluwatimileyinadigun2@gmail.com*
[(c)] *Ph.D., Associate Professor, Business Administration Programme, Bowen University, Iwo, Osun State, Nigeria; E-mail: johnson.olaosebikan@bowen.edu.ng*
[(d)] *Lecturer, Accounting Programme, Bowen University, Iwo, Osun State, Nigeria; E-mail: olafemidele@gmail.com*
[(e)] *Lecturer, Business Administration Programme, Bowen University, Iwo, Osun State, Nigeria; E-mail: john.ajani@bowen.edu.ng*

ARTICLE INFO

Article History:

Received: 1st March 2022
Accepted: 24th April 2022
Online Publication: 29th April 2022

Keywords:

Ads Based On Users' Interest, Ads Intrusiveness, Behavioural Targeting Click-Through Intention, Perception

JEL Classification Codes:

M13, M31, M37

ABSTRACT

This study assessed the effect of adverts (Ads) based on users' interest, Ads intrusiveness on the perception of behavioural targeting and click-through intention. The study further examined how the perception of behavioural targeting mediates the interaction between Ads based on users' interest, Ads intrusiveness and click-through intentions. The study was a descriptive survey, and the approach was deductive. The study collected primary data from a sample of 376 internet users in Nigeria using a cloud-based questionnaire. The data obtained were analysed using descriptive and inferential statistical tools. Partial least square structural equation modelling (PLS-SEM) was used to test the hypotheses. Findings showed that Ads based on users' interest and Ads intrusiveness predict click-through intentions and the perception of behavioural targeting. Perception of behavioural targeting mediated the interaction between Ads based on users' interests and click-through intentions. Overall, the study concluded that Ads based on users' interest and Ads intrusiveness influences the perception of behavioural targeting, which affects click-through intention. Hence the study recommended that digital entrepreneurs carefully design, manage and control the Ads contents they direct to customers. Digital entrepreneurs should exercise caution in implementing their behavioural targeting strategy so as not to breach an acceptable threshold.

INTRODUCTION

Consumer needs vary significantly across social, economic, demographic, and geographical dynamics. For decades, businesses have faced the challenge of satisfying each need as doing so will mean creating numerous varieties of a product and varying marketing strategies. In the same way, it has also been impossible to direct customized Ads to each customers' needs using the traditional offline marketing approach. However, in the wake of technological advancement (Helberger et al., 2020), the internet has evolved into a significant business vehicle allowing businesses have a wider reach at relatively lesser cost and more incredible speed. The internet has also gained popularity as an effective marketing tool because of its size, expected growth trajectory, broad demographics and the possibility of sharing information and resources worldwide (Ozcelik & Varnali, 2019).

The internet provides users with enormous access to information regarding brands, products and firms from across the globe in seconds (Kumar & Patel, 2014). The internet allows digital entrepreneurs to efficiently market and sell their products and services online (Kaspar et al., 2019). The rapidly growing *e*-commerce industry and upsurge of digital entrepreneurs worldwide indicate the growth and popularity of the internet and internet users (Fachryto & Achyar, 2018). We operationalize digital entrepreneurs as businesses who use online market platforms for marketing their products and services. Digital entrepreneurs leverage the technology that allows for trailing an internet user's surfing behaviour by using 'cookies' on the users' computer or saving a visiting internet user's computer IP address (Carrascosa et al., 2015; Dwyer, 2011). This technology monitors people's online behaviour, and digital entrepreneurs use the information collected to show

[1]*Corresponding author: ORCID ID: 0000-0002-2845-6021*

https://doi.org/10.46281/ijmri.v7i1.1702

To cite this article: Oladele, S., Adigun, O., Johnson, L. S., Oladele, F., & Ajani, J. (2022). BEHAVIOURAL TARGETING, PERCEPTION OF INTERNET USERS AND CLICK-THROUGH INTENTIONS: IMPLICATIONS FOR DIGITAL ENTREPRENEURS IN NIGERIA. *International Journal of Marketing Research Innovation*, *7*(1), 1-11. https://doi.org/10.46281/ijmri.v7i1.1702

people individually targeted advertisements (Bayer et al., 2020). This phenomenon is called behavioural targeting. Behavioural targeting has been referred to as online profiling (Lammers, 2020) and, in other cases, online behavioural targeting (OBA) (Varnali, 2019). Behavioural targeting has allowed digital entrepreneurs to reach out to a larger market using targeted Ads cost-effectively. Behavioural targeting is believed to be part of the future of advertising (Boerman et al., 2017) and is currently a significant discourse in research and practice. As of 2017, globally, investments in online advertising quickly rose to about 230 billion dollars (Kaspar et al., 2019) and exceeded $100 billion in 2018 in the United States (Bayer et al., 2020). Media agency Magna, in 2018, also reported that 44% of the aggregate advertising expenditure globally would be spent on digital media, with the most significant portion allocated to customized online Ads/behavioural targeting (Ozcelik & Varnali, 2019).

The underlying aim of behavioural targeting is for the targeted customer to spur intention to click the Ads and eventually make a purchase. Click through intention describes the willingness of a web user to click on a targeted ad. However, targeting is perceived as intrusive to people's privacy (Boerman et al., 2017). There are currently privacy concerns around the use of behavioural targeting, which has received much attention from digital entrepreneurs, consumers, policymakers, and scholars. The recent allegations against Cambridge Analytica using sensitive Facebook user data to customize Ads in boosting online promotions further points to the need for investigation into data-based customization of online Ads (Ozcelik & Varnali, 2019).

As a developing phenomenon, there are neither strong definitions of behavioural targeting nor an evident accumulation of empirical findings on the effect of Ads intrusiveness on the perception of behavioural targeting and advertising outcomes such as click-through intentions (Boerman et al., 2017), click-through ratio (Yan et al., 2009), sales conversion (Farahat & Bailey, 2012), purchase intention and actual purchases (Boerman et al., 2017; Fachryto & Achyar, 2018) and revenue (Beales, 2011; Breznitz & Palermo, 2013). Although behavioural targeting is expected to attract users' interest to more personalized and relevant Ad content, not so much is known about the effect of such behavioural targeting characteristics on the perception of behavioural targeting and advertising outcomes.

Specifically, there is no consensus as to how developing Ads that appeal to users' interests and Ads that target users' earlier browsing usage affects the perception of users about behavioural targeting and how this perception, in turn, impacts expected behavioural targeting outcomes such as click-through intention (Boerman et al., 2017). Particularly in Nigeria, there seems to be a dearth of literature on behavioural targeting and its effect. In an attempt to bridge that empirical gap, this study sought to examine online advertising dynamics using behavioural targeting empirically. We sought to answer the following questions: *What are the direct effects of Ad intrusiveness and Ads based on users' interest in click-through intentions? What is the relationship between ad intrusiveness and users' perception of* behavioural targeting*? How do Ads based on users' interest affects users' perception of behavioural targeting? To what extent does the perception of* behavioural targeting *predict click-through intention?*

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Behavioural Targeting and Click-Through Intentions

Almost two decades ago, visionaries (Hariharan et al., 2015; Kenny & Marshall, 2000) foretold that developments in technology would transform marketing practices through digital mediums to the point where marketers would be able to reach the right customer at the right time (Ozcelik & Varnali, 2019). Based on current developments, perhaps this may be the fulfilment of that prophecy as we witness a paradigm shift from traditional means of marketing to online advertising, particularly behavioural targeting. The concept of behavioural targeting as a relatively new concept (Breznitz & Palermo, 2013) is an online advertising practice that gathers information regarding web users' interests and incorporates the same in designing and tailoring Ads (Carrascosa et al., 2015). Koskinen (2017) regarded behavioural targeting as an internet-based advertising strategy, making use of a collection of data mining algorithms to track the browsing behaviour of internet users and, based on the browsing pattern (Bayer et al., 2020), direct online Ads to individuals with a higher tendency to be interested in the advertised product or service. In many cases, browsers are unaware that they are being tracked as the tagging is mostly invisible, and the data is collected anonymously. This tracking is made possible using cookies (that is, little files dropped on the users' hard drive while they surf the net) (Ozcelik & Varnali, 2019).

Major digital entrepreneurs use cookies to track the web-browsing pattern of users and direct those users with content likely to be of interest and relevance to a specific consumer to increase Ads effectiveness, which is expected to lead to higher click-through and higher revenue for the publisher, the aggregator and the entrepreneur by making a sale. Carrascosa et al. (2015) regarded this strategy as network-based targeting. Digital entrepreneurs engage in the use of behavioural targeting under the presumption that consumers will be receptive to Ads specially tailored to their needs, interest, and browsing history (Boerman et al., 2017; Kumar & Patel, 2014; Schedwin, 2008). Kumar and Patel (2014), for example, found that targeted Ads that kept in view the interest of the internet users and their browsing history were more likely to get positive responses (click through), consolidating the claim of Kaspar *et al.* (2019) who reported that attention for personally relevant advertisement can be strong. Yan et al. (2009) also provided an empirical investigation on the click-through log of advertisements retrieved from a commercial search engine which showed that click-through rates can be averagely increased by 670% by properly segmenting web users based on their short-term online behaviour for behavioural targeting. So, we hypothesize that:

H_1: Ads based on users' interest positively affects the internet users' click through intentions

However, there is a flip side to this assumption, as there are privacy intrusion issues relating to the use of behavioural targeting. According to Ozcelik and Varnali (2019), the online behavioural targeting strategy in advertising is one of the most debated contemporary issues relating to data privacy in the information era. Privacy concern is defined as "the degree of consumers' concern about potential privacy intrusion" (Li & Huang, 2016). There is a clear-cut distinction between what consumers consider valuable and what they perceive to be excessively intrusive. Breaching this line can prompt users to apply blocking software for cookies and Ads or result in attracting firm regulatory interventions (Dwyer, 2011). This was the case in Ozcelik and Varnali (2019), that found that perceived security risk associated with clicking customized online Ads had a directly inverse effect on the perception of informativeness and entertainment of targeted Ads. The work of Fachryto and Achyar (2018) reiterated that intrusiveness of Ads had an adverse effect on the attitude of customers and their purchase intention. Li and Huang (2016) also established that concerns for privacy makes online consumers resist behavioural targeting. So we hypothesize that:

H_2: Ads intrusiveness negatively affects click-through intentions

Behavioural Targeting, Perception, and Click through Intentions

There is a close and strong link between perception and attitude (Pickens, 2005), and according to Fish (2010), perception is a mental phenomenon- the process leading to the production of meaningful disposition towards a product or a firm by interpreting and organizing sensation (Pickens, 2005). The feeling or interpretation may be real or perceived (Kondalkar, 2007; Pickens, 2005). Perception is underscored in the acquisition of beliefs (Fish, 2010) and is considered the most influential determinant of attitude about an object (behavioural targeting) (Kalra et al., 2016). By implication, the success of the behavioural targeting strategy is determined, in part, by how it is perceived by internet users (Alnahdi et al., 2014). This is because the strategy's success revolves around internet users and their feelings about the various attributes of the strategy.

Pickens (2005) identified four major stages in perceptions, namely: *stimulation* (taste, smell, see, hear, and touch); *registration* (selection of positive or negative feedback); *organization* (drawing upon prior experience) and *interpretation* (analysis and understanding based on beliefs and prior experience). Ebrahim (2013) submitted that customers hold perceptions about certain elements such as price, appearance, and attributes which in turn shape their disposition towards an object (behavioural targeting). He related that the choice or preference of the customer or prospect would be based on (in part) the value placed on the above elements. These notions have also found support in the literature. Alnahdi *et al.* (2014), for instance, noted that concerns for privacy and the characteristics of targeted Ads significantly affected the perception of behavioural targeting. Based on these, we carved out three hypotheses:

H_3: Ads based on users' interest positively shape the perception of internet users about behavioural targeting.
H_4: Ads intrusiveness negatively shapes the perception of internet users about behavioural targeting.
H_5: A positive perception of behavioural targeting positively and significantly affects click-through intentions.

Some studies have also considered the perception of behavioural targeting as mediating the link between targeted Ads characteristics and Ads outcome such as purchase intention. For example, Fachryto and Achyar (2018) on the Indian e-marketplace showed that perceived Ad intrusiveness positively affected the perceived threat of behavioural targeting and led to a negative attitude toward the Ad and subsequently adverse purchase intention of products displayed using behavioural targeting. Similarly, Lammers (2020) revealed that perceived ads intrusiveness resulted in a negative attitude towards brands that use behavioural targeting strategy. Li and Huang (2016), on the other hand, related that Ads that are perceived to be personalized positively shape the perception of behavioural targeting, eventually leading to favourable responses, including click-through intention (Kumar & Patel, 2014). So we hypothesize that:

H_6: The perception of behavioural targeting mediates the relationship between Ads based on users' interest and click-through intentions.
H_7: The perception of behavioural targeting mediates the relationship between Ads intrusiveness and click through intentions.

Theoretical Framework

The study is underlined in the theory of planned behaviour (TPB). TPB is very influential and one of the most common theories today that focuses on understanding or predicting human intention to perform a particular behaviour (Dai, 2012; Ajzen, 2015). TPB regards "*intention*" as the immediate antecedent of a particular behaviour, that is, the most important predictor of an individual's behaviour. According to Ajzen (2015), TPB provides an alternative approach to understanding consumers' decision making. The theory proposes three conceptual determinants of intention: attitude towards the behaviour/behavioural beliefs, perceived behavioural control/control beliefs, and subjective norm/normative beliefs. The behavioural beliefs relate to the perception and appraisal of a behaviour (Dai, 2012), the normative belief revolves around social pressures to perform a behaviour and the individuals' disposition or motivation to accede to the social pressure (Ajzen, 2015), while the control belief is the perception of the individual as to how easy or difficult performing a behaviour can be. This perception is usually drawn from experience and expected barriers or impediments (Dai et al., 1995, 2007; Dai, 2012; Ajzen, 2015).

The theory opines that if the degree to which the three components are favourable is high, the individual will exhibit a higher intention to perform a behaviour under consideration and vice versa. Digital entrepreneurs must therefore coin their targeted Ads in such a way that the information is useful in creating a positive impression about the brand without placing negative pressure on the targeted customers to spur intention to react and behave favourably to the targeted Ads.

METHODS

Research Design, Population, and Sample Size

This study is an applied research adopting the survey research method as adopted by related works (Alnahdi et al., 2014; Kumar & Patel, 2014; Smit et al., 2014). Specifically, this study sought to address issues in behavioural targeting as a tool for online advertising. Applying the survey method to this kind of study allowed a large amount of data to be collected, afforded flexibility, and permitted quantitative analysis (Olayiwola, 2007). Using primary data, the study employed the use of a close-ended questionnaire (online survey) to source data from internet users. The online survey is considered most appropriate for a study that focuses on "online advertising". The population for this study comprises internet users in Nigeria. Given the unit of analysis for this study being internet users, the specific number of internet users, according to Statista (2018), was 92.3 million. Using the Taro Yamane formula for determining the sample size, the estimated sample size was 399.99, approximately 400.

Data Collection and Measurement of Variables

The link to the online survey (https://forms.gle/tpvQrJfG56X6f2nZ9) was tested first by carrying out a pilot study. The links were shared with thirty internet users to ensure that there were no complications with accessing the survey instrument. When entries were retrieved, and corrections were effected, the final link was uploaded on the researchers' WhatsApp status and group pages, Telegram, Facebook pages, Instagram, Twitter and LinkedIn. The survey was consistently promoted for a period of close to 10 months (April 16, 2019, to January 7, 2020) to ensure it reached as many respondents as possible.

The questionnaire for this study included items and scales from the works of Ducoffe (1995), Gauzente (2009); Kumar and Patel (2014); Boerman et al. (2017); and Ozcelik and Varnali (2019). The questionnaire comprised five sections. Section A covered the respondents' demographic characteristics. In section A, the question "do you reside in Nigeria" was asked to ensure that only respondents who resided in Nigeria participated in the study. Respondents who did not meet the eligibility criteria were redirected to quit the survey. Section B focused on Ads intrusiveness; section C addressed Ads based on users' interest; section D, perception of behavioural targeting; and section E measured users' click-through intention.

Table 1. Description of variables and sources of questionnaire items

Variables	Category	Description	No. of items	Authors
Click through intention	DV	Is a measure of the extent that a user is likely to click on a targeted Ads	2	Gauzente (2009); Boerman et al. (2017)
Perception of behavioural targeting	MV	Is a measure of how internet users perceive BT (+/-)	3	Ducoffe (1995); Boerman et al (2017)
Ads based on users' interest	IV	Popup Ads based on earlier likes and dislikes	3	Kumar and Patel (2014); Boerman et al. (2017)
Ads intrusiveness	IV	Relating to privacy infringements	3	Ozcelik and Varnali (2019)

Note: IV, independent variable; MV, mediating variable; DV, dependent variable; BT, behavioural targeting

Method of Data Analyses

Descriptive analysis (frequency distribution) was employed for the first section of the survey, which captured the respondents' demographic information. Variance-based estimations was carried out using Partial least square structural equation modelling to test the hypotheses. PLS-SEM is gaining appreciable use in management science as a second-generation multivariate statistical procedure that allows for analysing complex interrelationships between variables simultaneously (Benitez et al., 2020). Using the PLS-SEM technique required several procedures, including assessing the measurement model and the structural model (Hair et al., 2019). Assessing the measurement model included estimating the construct (standardized factor loading), discriminant (heterotrait-monotrait) and convergent validity (Average variance extracted). The internal consistency test (Composite reliability and Rho_A) was also carried out. Assessing the structural model included estimating the model fit (standardized root mean square residual (SRMR), the Root Mean Square Residual Covariance (RMS_{theta}), the normed fit index (NFI; also referred to as the BentlerBonett index); the overall model fit (d_{ULS}, and d_G) as recommended in Benitez, Henseler, Castillo, and Schuberth (2020); predictive relevance (Hair et al., 2013) and $PLS_{predict}$ statistics (Shmueli et al., 2019).

RESULTS

The first response was recorded on April 16 2019, at about 10:35:05 AM GMT +1. The survey was closed on January 7 2020, at 8:09:46 PM GMT +1. This section presents the findings from the data gathered and analysed.

Demographics

Table 2. Demographics

Measure	Data	Frequency	%
Gender	Male	231	61.4
	Female	145	38.6
Age bracket	Less than 18 years	4	1.1
	18-25 years	182	48.4
	26-33 years	114	30.3
	34-41 years	49	13.0
	42-49 years	24	6.4
	50 years and above	3	.8
Academic Qualification	SSCE	59	15.7
	Diploma (ND)	13	3.5
	Undergraduate	233	61.9
	Post Graduate	71	18.9
Occupation	Private firm workers	89	23.7
	Civil servants	52	13.8
	Unemployed	3	0.8
	Entrepreneurs	79	21.0
	Clergy	1	0.3
	Youth Corps Members	12	3.2
	Military	1	0.3
	Lecturer	2	0.5
	Student	133	35.3
	Consultants	3	0.8
	Military	1	0.3
n= 376			

Source: Field survey (2020)

The respondents were asked to indicate their gender, of which 231(61.4%) indicated male, meaning higher responses from the male gender. This may support the findings of Sax et al. (2003) that claimed that the male gender is more likely to respond positively to online surveys than the female gender. The dominant age group that responded to the study was the 18-25 years group, 182(48.4%), while 114 (30.3%) entries were from respondents between the ages of 26-33 years. Based on the age group result, it is not surprising that most of the respondents, that is, 233(61.9%), were undergraduates, which consolidated the result on the occupation, with 133(35.3%) of the respondents indicating they were students. The flow of the results shows that much of the internet activities are performed by the younger generation.

Assessment of Measurement Model

The measurement model was assessed using descriptive statistics (mean and standard deviation), construct validity (standardized factor loadings), convergent validity (average variance extracted), discriminant validity (heterotrait-monotrait criterion) and internal consistency (Rho_A, composite reliability). The variance inflated factors (VIF) was also estimated for multicollinearity issues.

Individual Item Reliability

The threshold for standardized factor loadings was over .70. One of the items (AD3) fell short with a factor loading of 0.577. Although this is below the .70 threshold, the item was retained from a content validity viewpoint (Garson, 2016). Secondly, as Benitez et al. (2020) suggested, two analyses were performed to determine the effect of either retaining or removing the item. The first analysis excluded the item, and the second analysis included the item, and the difference in results was not significant. Based on the recommendations of Benitez et al. (2020), the item was retained.

Internal Consistency Reliability

Table 3. Descriptive statistics, construct validity, convergent validity, and reliability

Constructs	Items Code	M	Std.D	SFLs	VIF	RhoA	CR	AVE
				≥ .70	**< 5**	**≥ .70**	**≥ .70**	**≥ .50**
Click through intentions	CT1	3.15	1.05	0.897*	1.709	0.788	0.902	0.822
	CT2	3.37	1.09	0.915*	1.709			
Ads intrusiveness	AD1	3.53	1.06	0.840*	1.281	0.722	0.801	0.579
	AD2	3.41	1.05	0.835*	1.412			
	AD3	3.43	1.10	0.577*	1.233			

Ads based on interest	Int1	3.64	1.00	0.803*	1.45	0.727	0.844	0.643
	Int2	3.58	0.98	0.847*	1.589			
	Int3	3.45	1.00	0.753*	1.324			
Perception of behavioural targeting	P1	3.05	1.01	0.860*	1.934	0.826	0.896	0.741
	P2	2.89	1.04	0.869*	1.982			
	P3	3.39	0.97	0.853*	1.742			
***Significant at 95% confidence level**								

Source: Field Survey (2020)

The composite reliability was also estimated for testing internal consistency. As suggested in Ringle et al. (2018), the threshold for CR should be greater than 0.7 but less than 0.95, especially for confirmatory research (Garson, 2016). From table 3, all the constructs fulfilled this criterion of reliability. Meanwhile, the recent view of PLS-SEM suggests that rather than relying on Cronbach's alpha (too conservative) and CR (too strict and liberal) (Hair et al., 2019), one should consider using the "rho_A" coefficient to assess the reliability of the PLS construct scores, as defined in Dijkstra and Henseler (2015). The rho_A as a test of reliability has a recommended threshold of 0.70. However, a rho_A value above 1 is abnormal (Jain, 2019). It can be observed that all the constructs satisfy the conditions of rho_A. Hence it can be concluded that the measurement model is reliable.

Convergent Validity

Convergent validity assumes that construct measures that ought to be related to each other theoretically are related to each other. The average variance extracted (AVE) is used to determine convergent validity. A threshold of .50 is desirable for the AVE when testing for convergent validity. The implication is that the construct explains an average of at least 50% of its items' variance. From the AVE values in table 3, the criterion was satisfied for all the constructs.

Multi-Collinearity

Assessing collinearity usually involves estimating each item's variance inflation factor (VIF). Different thresholds for VIF values have been recommended. However, VIF within 5 shows evidence of no multicollinearity (Benitez et al., 2020; Moreno & Casillas, 2008; Soares & Perin, 2019). The study calculated the VIF for all of the variables in the model to test for multicollinearity. This was done to avoid multicollinearity disturbance. For the study variables, the VIF values fall within the recommended threshold of <5 (Ringle et al., 2018). The variable with the highest VIF value was P2, with a VIF of 1.982, and this indicates no concerns regarding multicollinearity *(see table 3)*.

Table 4. Heterotrait-monotrait ratio

Variables	Ads Intrusiveness	Click through intentions	Ads based on Interest	Perception of BT
Ads Intrusiveness				
Click through intentions	0.422			
Interest	0.145	0.47		
Perception	0.465	0.825	0.485	

Note: Shaded boxes are the standard reporting format for the HTMT procedure
Source: SmartPLS 3output (Field survey, 2020)

Discriminant Validity (Heterotrait-Monotrait)

The Fornell-larcker criterion has been criticized for not detecting discriminant validity in common research situations reliably (Henseler et al., 2015). Henseler et al. recommended a substitute approach to test for discriminant validity: the heterotrait-monotrait criterion (HTMT), which was adopted in this study. The method specifies that if the HTMT value is greater than the $HTMT_{.85}$ value of 0.85 (Kline, 2011), discriminant validity is an issue, especially if the constructs are conceptually more distinct (Ringle et al., 2018). Table 4 shows that none of the values was higher than 0.85, indicating adequate discriminant validity.

Assessment of Structural Model

The structural model for the study was assessed for model fit, predictive relevance and the $PLS_{predict}$ statistics as recommended in Hair et al. (2019).

Model Fit and Predictive Relevance

Table 5. Model fit/predictive relevance

Model fit	Value	Benchmark	Source
SRMR	0.076	< 0.08	Garson (2016)
NFI (Bentler-Bonett index)	0.702*	> .90	Benitez *et al* (2020)
Rms_theta	0.252*	< 0.12	(Ali et al., 2016)
R^2 (Click through)	0.466	0.26	Cohen (1988)
(Perception of BT)	0.278		

Q^2 (Click through) (Perception of BT)	0.369 0.198	>0, 0.25 and 0.50 depict small, medium and large predictive accuracy respectively	Hair *et al.* (2019)
		HI_{95}	
d_{ULS} (d_{ULS}<HI_{95})	0.183	0.218	Benitez *et al.*, 2020
d_G (d_G<HI_{95})	0.158	0.168	Benitez *et al.*, 2020

*Did not meet the model fit conditions
Source: SmartPLS 3 output, Field survey (2020)

The model fit tests included estimating the SRMR, NFI, Rms_theta, and overall model fit using d_{ULS}, and d_G (See table 5). The predictive relevance estimation included R square (R^2) and Stone-Geisser's (Q^2) value (see table 5). Some of the measures of goodness of fit were seen not to meet the benchmark, such as NFI and Rms_theta. However, Ali, Gon, and Ryu (2016) and Benitez et al. (2020) recommended that the values should not be strongly relied on as the goodness of fit measures are still developing. Meanwhile, other goodness of fit measures and predictive relevance met the criteria. The R^2 of 0.278 indicates that a 27.8% variation in the perception of behavioural targeting is accounted for by Ads intrusiveness and Ads based on users' interests. The R^2 value of 0.466 indicates that the perception of behavioural targeting accounts for a 46.6% variation in click-through intentions. The Q^2 of 0.369 shows a medium predictive accuracy for click-through intentions, while the Q^2 value of 0.198 shows more than small (>0) but less than medium (>0.25) predictive accuracy for the perception of behavioural targeting.

$PLS_{predict}$ Statistics

Table 6. $PLS_{predict}$ statistics

	PLS-SEM Statistics		**Linear regression model (LM)**	
	RMSE	Q²_predict	RMSE	Q²_predict
CTii	0.98	0.196	0.988	0.183
CTi	0.965	0.152	0.972	0.139
Pi	0.92	0.172	0.924	0.163
Pii	0.927	0.2	0.938	0.181
Piii	0.865	0.206	0.874	0.191

Source: SmartPLS output (2020)

To further assess the structural model, Hair et al. (2019) suggested the need to estimate the out-sample predictive power of the structural model. According to them, the R^2 only estimates the in-sample explanatory power without saying anything about the out-of-sample predictive power. To address this concern, a set of actions was recommended for out-of-sample prediction involving the estimation of the model on an analysis (that is, training) sample and evaluating its predictive performance on data other than the analysis sample, otherwise called the holdout sample (Shmueli et al., 2019). The estimation generated the prediction statistics (Root mean squared error [RMSE], Mean Average Error [MAE]) and $Q^2_{predict}$ statistics. Hair et al. (2019) suggested reporting the $Q^2_{predict}$ values first. According to them, $Q^2_{predict}$ values > 0 indicate that the model outperforms the most naïve benchmark (i.e., the indicator means from the analysis sample). As shown in Table 6, the $Q^2_{predict}$ values for all the indicators were positive, indicating they outperformed their naïve LM benchmark. By implication, the model has adequate predictive power. As recommended in Hair *et al.* (2019), RMSE was used instead of the MAE as the MAE is recommended for use only when or if the prediction error distribution is highly non-symmetric (Hair et al., 2019). To interpret the RMSE results, Hair *et al.* (2019) explained that the RMSE value is compared with the LM value of each indicator.

According to Hair et al. (2019), if the minority (or the same number) of indicators in the PLS-SEM analysis yields higher prediction errors than the naïve LM benchmark, this indicates a medium predictive power. If most of the indicators produce values higher than the LM benchmark, it means a weak predictive power, and if none of the indicators yields values higher than the LM benchmark, it indicates a high predictive power (Hair et al., 2019). As shown in Table 6, none of the indicator values yielded higher than the LM benchmark, indicating a high predictive power.

Hypothesis Testing

Table 7. Structural Estimates

Structural estimates (Hypotheses testing)				**Decision**
Path	***β***	***t*-value**	***f^2***	
H1: Ads Interest→CTI	0.142	2.927*	0.032	Supported
H2: Ads Intrusiveness →CTI	-0.103	2.374*	0.017	Supported
H3: Ads Interest→BTPercept	0.374	7.179*	0.193	Supported
H4: Ads Intrusiveness→ BTPercept	-0.370	7.478*	0.190	Supported
H5: BTPercept → CTI	0.574	11.970*	0.445	Supported
H6: Ads Interest→ BTPercept → CTI	0.214	5.830*		Supported
H7: Ads Intrusiveness → BTPercept → CTI	-0.212	6.163*		Supported

Note: *1.96 (p<0.05)
Source: SmartPLS output (Field survey, 2020)

The effect size (f^2) that shows the size of an effect was also calculated (see table 7). The effect size cushions the limitation of the *p*-value, which shows just the significance of the relationships. Cohen (1988) recommended a 0.02 threshold for small effects, 0.15 for medium effects and 0.35 for large effects (see table 7). The results for the test of hypotheses are shown in table 7 and figure 1. Concerning the test of hypotheses, Ads based on users' interests had a positive effect on click-through intentions ($\beta = 0.142; t = 2.927; f^2 = 0.032;\ p < 0.05$) supporting hypothesis one. Ad intrusiveness was found to have a significant and negative effect on click-through intention ($\beta = -0.103; t = 2.374; f^2 = 0.017;\ p < 0.05$). This means that hypothesis two is supported. Ads based on users' interests had a positive effect on the perception of behavioural targeting ($\beta = 0.374; t = 7.179; f^2 = 0.193;\ p < 0.05$). Hence, hypothesis three is supported. Ads intrusiveness had a negative effect on the perception of behavioural targeting ($\beta = -0.370; t = 7.478; f^2 = 0.190;\ p < 0.05$). Hence hypothesis four is supported.

Perception of behavioural targeting was found to significantly and positively influence click-through intentions ($\beta = 0.574; t = 11.715; f^2 = 0.445;\ p < 0.05$). As such, hypothesis five is supported (see table 7 and Figure 1). Hypothesis six was also supported as the perception of behavioural targeting partially mediated the relationship between Ads based on users' interest and click-through intention ($\beta = 0.214;\ t = 5.830;\ p < 0.05$). The relationship between Ads intrusiveness and click through intention was also found to be partially mediated by the users' perception of behavioural targeting ($\beta = -0.212;\ t = 6.163;\ p < 0.05$).

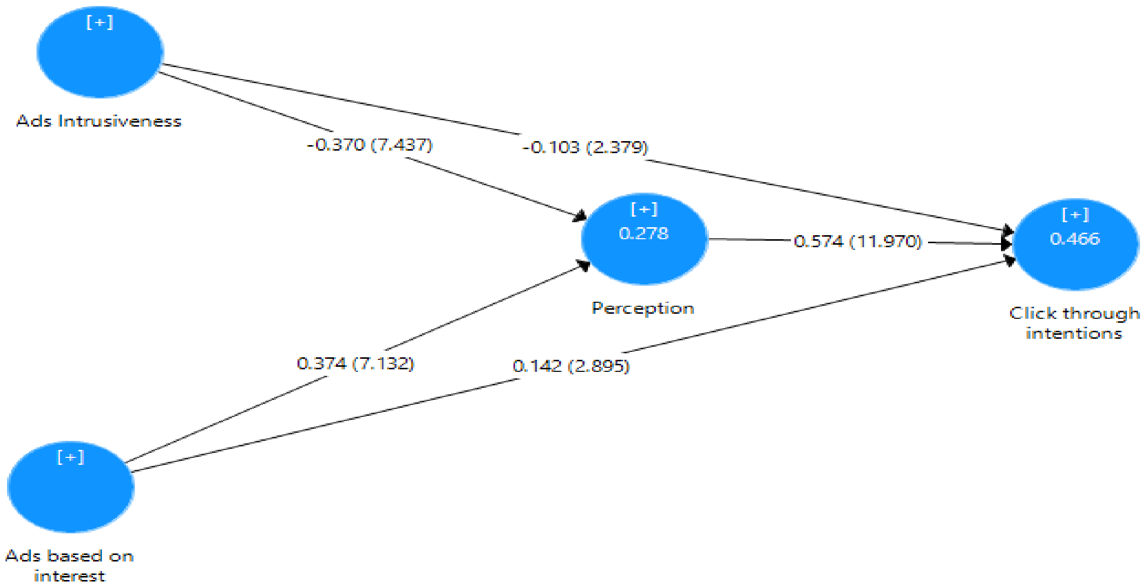

Figure 1. Structural model (path coefficients and t-values)
Source: SmartPLS output (Field survey, 2020)

DISCUSSIONS

In line with extant literature (Li & Huang, 2016; Ozcelik & Varnali, 2019), we found a direct inverse and significant relationship between Ads intrusiveness and click-through intention ($\boldsymbol{\beta}$ = -0.102; p<0.05). However, here, the effect of Ad intrusiveness on the perception of behavioural targeting ($\boldsymbol{\beta}$= -0.370) was stronger than the direct effect of Ad intrusiveness on click-through intention. Similarly, Lammers (2020) observed that though privacy concerns were present and strong among the users of the internet, it did not have a direct effect on the attitude towards the brands that used the behavioural targeting strategy. Although our study found a direct impact, we see the effect stronger on perception than intention. This was subsequently confirmed as we found that the perception of behavioural targeting strongly mediated the relationship between Ads intrusiveness and click-through intention.

Our result also suggests that Ads based on users' interests had a stronger direct and positive effect on click-through intention ($\boldsymbol{\beta}$ =0.142; f^2= 0.032) than Ads intrusiveness which is consistent with Kumar and Patel (2014). This confirms the statement made by Zuckerberg (2007) cited in Wiese et al. (2020) that "advertising works when it is in line with what people are already trying to do". We see this play out in the study as the effect Ads based on users' interest exert directly on perception and click-through intentions were stronger than perceived Ads intrusiveness. However, similar to Ads intrusiveness, we find that the effect of Ads based on users' interest on the perception of behavioural targeting was much stronger ($\boldsymbol{\beta}$=0.374; f^2= 0.193). Overall, we find that internet users' perception of behavioural targeting had the strongest direct effect on click-through intentions ($\boldsymbol{\beta}$ = 0.574; f^2=0.445). This indicates that the stronger the positive perception of behavioural targeting the stronger the tendency to click on targeted Ads when they pop up.

The strength of the effect of perception on click-through intentions was as a result of the effect of Ads based on users' interest and Ads intrusiveness. This inference is made in line with the results we found from the mediation analysis. For Ad intrusiveness, the $\boldsymbol{\beta}$ was negative (-0.214), indicating that the mediation effect was negative. This is in line with the negative effect of Ad intrusiveness on the perception of behavioural targeting. This may imply that as internet users increasingly sense privacy intrusion, their perception of behavioural targeting gravitates towards the negative spectrum, threatening the tendency to want to click on targeted Ads. The result confirms the report of Fachryto and Achyar (2018) on the e-marketplace of India. Their study showed that the perceived threat of behavioural targeting resulting from privacy concerns increased online customers' negative attitudes, eventually leading to negative purchase intentions.

On the other hand, the result points to a positive mediation in the case of Ads based on users' interest and click-through intention, which resonates with Alnahdi et al. (2014), showing that targeted visible Ads and characteristics of targeted Ads significantly affected the perception of behavioural targeting of students in Europe and Asia. This also supports the argument of Kalra et al. (2016), expressing that perception is one of the most influential factors that shape attitude towards a phenomenon. The work of Ebrahim (2013) further corroborated this position. Alnahdi et al. (2014), as a result, suggested that for digital entrepreneurs to positively improve the perception of behavioural targeting, the characteristics of targeted Ads can be made more attractive to contain relevant content. This would require ensuring a higher level of control over the features of the targeted ads to make them more valuable for the consumers to lessen concerns about intrusion of privacy.

IMPLICATIONS FOR THEORY AND PRACTICE

The study findings have implications for policy, theory, and practice. From a theoretical point of view, our result is consistent with the theory of planned behaviour as we observed that content relevant Ads targeted at customers positively shape their perception of behavioural targeting and, in turn, influences click-through intentions. TPB regards "*intention*" as the immediate antecedent of a particular behaviour. In other words, it is a critical determinant or predictor of an individual's behaviour. Although our analysis did not go beyond examining the intentions to click on targeted ads, based on TPB, strong and positive intentions to click on Ads will likely result in actual click-through, especially when the perception about behavioural targeting is positive.

From the study findings, there is a call for policy regulation in terms of the activities of digital entrepreneurs and publishers regarding privacy intrusion. There is a need to create boundaries and ensure proper control and monitoring of online advertising activities to ensure compliance and reduce the tension created by internet users' concerns about privacy intrusion. Digital entrepreneurs, on their part, may want to be cautious with the possible implication of a high level of privacy concern amongst internet users in shaping their perception of behavioural targeting. As shown in the study, a negative perception of behavioural targeting likely results in increased avoidance of targeted Ads. The Ads become ineffective if a high percentage of targeted customers continue to avoid taking a second look at the Ads. Hence the need for proper control.

In the wake of technological advancement, and the shift from traditional advertising methods to online advertising, potential and existing digital entrepreneurs would need to understand the most effective ways to engage their customers with relevant Ad content. Digital entrepreneurs can use the information from this study to design, manage and control their Ad contents to ensure they reflect the customers' needs without triggering thoughts and concerns about privacy intrusion.

CONCLUSIONS AND RECOMMENDATIONS

The study confirmed the positive and significant effect of Ads based on users' interest in the perception of behavioural targeting and click-through intentions. It also showed the negative effect of Ad intrusiveness on the perception of behavioural targeting and click-through intentions. We conclude that the perception of behavioural targeting influences click-through intention. We also conclude that the perception of behavioural targeting is shaped by Ad intrusiveness and Ads based on users' interests. While one (Ads intrusiveness) shapes the perception of behavioural targeting negatively, the other (Ads based on users' interest) positively shapes the perception of behavioural targeting. Overall, we conclude that the perception of behavioural targeting partially mediates the link between Ads based on users' interest, Ads intrusiveness and click-through intention.

So we recommend that digital entrepreneurs carefully design, manage and control the Ads contents they direct to customers. Those Ads must be in line with the needs and interests of the customers. This way, the customers will have a higher tendency to be favourably disposed to the Ads and likely click on them. Digital entrepreneurs would have to exercise caution in implementing their behavioural targeting strategy so as not to breach an acceptable threshold where privacy concern becomes a principal determinant of a targeted customers' disposition towards an Ad and/or the brand. Obtaining customer data from the brand's own website or source, for instance, is less creepy and would not trigger a sense of intrusion.

Limitations and Suggestion for Further Studies

We acknowledge some limitations surrounding our study, and these gaps we believe provides an avenue for subsequent studies to fill. As noted in the discussion, our study did not go beyond "click-through intention". Although we expect that intention in line with the theory of planned behaviour is a precursor to behaviour, empirical backings are needed to either support or refute the assertion within the context of this research. Secondly, a number of Ads effectiveness measures were not captured in this study, including click-through ratio, purchase intention, and actual purchase, among others that future researchers can look into. The majority of the respondents are students and are young. This category of respondents tends to be more favourably disposed to technology compared to the average population. Considering demographic disparities might reveal interesting findings that will be useful to the body of knowledge. Finally, our proxies of behavioural targeting are not quite exhaustive. Ads based on browsing history, for instance, was not covered in this study.

Author Contributions: Conceptualisation, S.O. and O.A., Data Curation, S.O., Formal Analysis, S.O. and L.S.J., Funding Acquisition, S.O., O.A., L.S.J., F.O. and J.A., Investigation, S.O. and O.A., Methodology, S.O. and F.O., Project Administration, L.S.J. and F.O., Resources, S.O., O.A., L.S.J., F.O. and J.A., Software, S.O., Supervision, L.S.J. and F.O., Validation, F.O. and O.A., Visualisation, S.O., Writing-Original Draft, S.O., F.O., and O.A., Writing-Review and Editing, L.S.J., F.O., and O.A. Authors have read and agreed to the published version of the manuscript.

Institutional Review Board Statement: Ethical review and approval were waived for this study, due to that the research does not deal with vulnerable groups or sensitive issues.

Funding: The authors received no direct funding for this research
Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.
Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to restrictions.
Conflicts of Interest: The authors declare no conflict of interest.

REFERENCES

Ajzen, I. (2015). Consumer attitudes and behaviour: the theory of planned behaviour applied to food consumption. *Rivista Di Economia Agraria*, *70*(2), 121–138. https://doi.org/10.13128/REA-18003

Ali, F., Gon, W. K., & Ryu, K. (2016). The effect of physical environment on passenger delight and satisfaction: Moderating effect of national identity. *Tourism Management*, *57*, 213–224. https://doi.org/10.1016/j.tourman.2016.06.004

Alnahdi, S., Maged, A., & Alkayid, K. (2014). The effectiveness of online advertising via the behavioural targeting mechanism. *The Business and Management Review*, *5*(1), 23–31.

Bayer, E., Srinivasan, S., Riedl, E. J., & Skiera, B. (2020). The impact of online display advertising and paid search advertising relative to offline advertising on firm performance and firm value. *International Journal of Research in Marketing*, *37*, 789–804. https://doi.org/10.1016/j.ijresmar.2020.02.002

Beales, H. (2011). *The value of behavioural targeting*. Network Advertising Initiative (NAI).

Benitez, J., Henseler, J., Castillo, A., & Schuberth, F. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. *Information & Management*, *57*(2), 1–16. https://doi.org/10.1016/j.im.2019.05.003

Boerman, S. C., Kruikemeier, S., & Borgesius, F. J. Z. (2017). Online behavioural advertising: a literature review and research agenda. *Journal of Advertising*, *46*(3), 364–376. https://doi.org/10.1080/00913367.2017.1339368

Breznitz, D., & Palermo, V. (2013). *Big data, big profits? Understanding the role of targeting technologies as part of a mixed online advertisement strategy* (No.311).

Carrascosa, J. M., Cuevas, R., Mikians, J., Erramilli, V., & Laoutaris, N. (2015). I always feel like somebody's watching me: measuring online behavioural advertising. *CoNEXT 15 Proceedings of the 11th ACM Conference on Emerging Networking Experiments and Technologies*, 1–13.

Dai, F. (2012). *A model of network marketing business entrepreneurial performance*. University of Technology, Sydney.

Dai, F., Teo, S., & Wang, K. Y. (1995). *Identifying and measuring motivational factors in conducting network marketing business by Chinese immigrants* (pp. 1–23). University of Technology, Sydney.

Dai, F., Teo, S., & Wang, K. Y. (2007). *Performance of entrepreneurial Chinese immigrants in network marketing organisations* (pp. 1–20). University of Technology, Sydney.

Dijkstra, T. K., & Henseler, J. (2015). Consistent partial least squares path modeling. *MIS Quarterly*, *39*(2), 297–316.

Ducoffe, R. H. (1995). How consumers assess the value of advertising. *Journal of Current Issues and Research in Advertising*, *17*(1), 1–18.

Dwyer, C. (2011). *The effect of behavioural targeting on trust in E-commerce* (pp. 1–28). https://doi.org/http://ssrn.com/abstract=1801366

Ebrahim, R. S. (2013). *A Study of Brand Preference: An Experiential View*. Brunel University, London.

Fachryto, T., & Achyar, A. (2018). Effect of online behavioural advertising implementation on attitude toward Ad and purchase intention in Indonesian e-marketplace. *Sriwijaya International Journal of Dynamic Economics and Business*, *2*(2), 123–138.

Farahat, A., & Bailey, M. (2012). How effective is targeted advertising? *International World Wide Web Conference*, 111–120.

Fish, W. (2010). *Philosophy of Perception: A Contemporary Introduction*. Routledge.

Garson, G. D. (2016). *Partial least squares: Regression and structural equation models* (2016 Eds). Statistical Associates Publishing.

Gauzente, C. (2009). The intention to click on sponsored links-an analysis of the moderating role of prior knowledge. *Actes Du 25th Congre's International de l'AFM-Londres, 14 et 15 Mai 2009*, 1–18.

Hair, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2013). *A primer on partial least squares structural equation modelling (PLS-SEM)*. Sage Publications.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hariharan, V. G., Talukdar, D., & Kwon, C. (2015). Optimal targeting of advertisement for new products with multiple consumer segments. *International Journal of Research Marketing*, *32*, 263–271. https://doi.org/10.2139/ssrn.2555682

Helberger, N., Huh, J., Milne, G., Strycharz, J., & Sundaram, H. (2020). Macro and exogenous factors in computational advertising: Key issues and new research directions. *Journal of Advertising*, *49*(4), 377–393. https://doi.org/10.1080/00913367.2020.1811179

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115-135.

Jain, D. C. (2019). *Mastering partial least squares structural equation modeling (PLS-SEM) with SmartPLS in 38hours*. iUniverse.

Kalra, S., Kondepudi, M., & Sridharan, A. (2016). Consumer attitude towards network marketing in a global scenario. *Intercontinental Journal of Marketing Research Review*, *4*(12), 9–14.

Kaspar, K., Weber, S. L., & Wilbers, A. (2019). Personally relevant online advertisements: effects of demographic targeting on visual attention and brand evaluation. *PloS ONE*, *14*(2), 1–18.

Kenny, D., & Marshall, J. F. (2000). Contextual marketing: the real business of the internet. *Harvard Business Review*, *78*(6), 119–125.

Kline, R. B. (2011). *Principles and practice of structural equation modeling*. Guilford Press.

Kondalkar, V. G. (2007). *Organizational behaviour*. New Age International Publishers.

Koskinen, S. (2017). *Targeted social media advertising and consumer decision making in online buying behaviour*. Oulu business school.

Kumar, K., & Patel, A. (2014). A research paper on measuring effectiveness of online behavioural advertisements. *International Journal of Scientific Research and Management (IJSRM)*, *2*(12), 1825–1832.

Lammers, R. (2020). *Feeling targeted in a digital era: A study about the influence on online behavioural targeting on consumer attitudes*. University of Twente.

Li, W., & Huang, Z. (2016). The research of influence factors of online behavioural advertising avoidance. *American Journal of Industrial and Business Management*, *6*, 947–957. https://doi.org/10.4236/ajibm.2016.69092

Moreno, A. M., & Casillas, J. C. (2008). *Entrepreneurial orientation and growth of SMEs: a causal model* (pp. 507–528). Baylor University.

Olayiwola, A. . (2007). *Procedures in educational research*. Hanjim Publications.

Ozcelik, A. B., & Varnali, K. (2019). Effectiveness of online behavioural targeting: a psychological perspective. *Electronic Commerce Research and Applications*, *33*, 1–12. https://doi.org/10.1016/j.elerap.2018.11.006

Pickens, J. (2005). Attitudes and perceptions of individuals. In N. Borkowski (Ed.), *Organizational Behavior in Health Care* (pp. 43–76). Jones and Bartlett Publishers.

Ringle, C. M., Sarstedt, M., Mitchell, R., & Siegfried, P. G. (2018). Partial least squares structural equation modeling in HRM research. *The International Journal of Human Resource Management*, 1–27. https://doi.org/10.1080/09585192.2017.1416655

Schedwin, J. (2008). Behavioural targeting: issues involving the Microsoft-aquantive and google-doubleclick mergers, and the current and proposed solutions to those issues. *Journal of Law and Policy for the Information Society*, *4*(3), 710–730.

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). *Predictive model assessment in PLS-SEM: guidelines for using PLSpredict*.

Smit, E. G., Noort, G. Van, & Voorveld, H. A. M. (2014). Understanding online behavioural advertising: user knowledge, privacy concerns and online coping behaviour in Europe. *Computers in Human Behavior*, *32*, 15–22. https://doi.org/10.1016/j.chb.2013.11.008

Soares, M. C., & Perin, M. G. (2019). Entrepreneurial orientation and firm performance: An updated meta-analysis. *RAUSP Management Journal*. https://doi.org/10.1108/RAUSP-01-2019-0014

Statista. (2018). *Number of internet users worldwide: 2005-2018*.

Varnali, K. (2019). Online behavioural advertising: An integrative review. *Journal of Marketing Communications*, *00*(00), 1–22. https://doi.org/10.1080/13527266.2019.1630664

Wiese, M., Akareem, H. S., & Wiese, M. (2020). Determining perceptions, attitudes and behaviour towards social network site advertising in a three-country context social network site advertising in a three-country context. *Journal of Marketing Management*, *00*(00), 1–36. https://doi.org/10.1080/0267257X.2020.1751242

Yan, J., Liu, N., Wang, G., Zhang, W., Jiang, Y., & Chen, Z. (2009). How much can behavioural targeting help online advertising? *In Proceedings of the 18th International Conference on World Wide Web, WWW '09,* 261–270.

Publisher's Note: CRIBFB stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.