Effectiveness of Digital Display as an advertising channel: The role of depth of interaction in the Sale Conversion process

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[Abstract] There is enough research on the effectiveness of digital display as an advertising channel. All these studies treat a click on the display/banner ad as a binary event. This paper goes beyond the binary value of the click to study the subsequent actions taken by a user post clicking on a display/banner ad, referring to those actions as the depth of interaction, and testing if the depth of interaction is better able to predict the final outcome. A prescriptive research design was employed in the study to model users' exposure to the banner ads during the campaign, employing binary logistic regression analysis. The results of the study indicate that the depth of interaction is able to predict the outcome significantly better than just the clicks. The results also indicate that the device used, depth of pages visited, duration of time spent and recency of visit have a very high effect on the final outcome and controlling them can deliver better results to the advertiser.

[Keywords] Banner advertising, Conversion funnel, Digital display advertising, Depth of interaction, Logistical regression, Sales conversion

Introduction

Digital display advertising, also known as banner ad, has become a popular phenomenon in the present marketing scenario. It is the graphic advertisement on websites, apps, or the social media by means of banners and other formats which include text, images, audio, and video. The primary aim of display advertisement is to create awareness of the brand to site visitors. Such visitor may take further action in term of clicking on the ads, landing on the website of the advertiser, and completing a sale by buying on the website. Display advertising is unique from the rest of the website's content. Display banner ads have been around since the start of advertising on the internet. They were the first form of advertising on the internet in 1994 (LaFrance, 2014).

Display advertisements offer benefits to customers and the companies (Heitman, 2022). Following is some of the benefits of digital display advertising:

1. They're targeted.
2. They are visually appealing.
3. They reach consumers on the go.
4. They support retargeting.
5. They build brand awareness and increase visibility.
6. They complement other marketing strategies.
7. They can block the competition.
8. They can be tracked easily for effectiveness.

Click through rates (CTR), a measure of effectiveness of any ad format on the internet, measures how frequently a viewer acts on an ad. The CTR of banner ads have been declining over the years from an average of 3% in mid-90s to half a percentage in the early 2000s (Meskauskas, 2001) and then to 0.28% in the quarter one of 2003 (DoubleClick, 2003). CTR of banner ads reached such low levels that Google Display Network, the biggest player in the market, stopped publishing this data (Swant, 2018). The last

reported average CTR of all banner ad format was 0.05% in 2018 (Chaffey, 2022).
This has led to many managers often questioning the "effectiveness of online display channel" in influencing customer behavior. According to Terlep et al., 2012, "In 2012, General Motors, terminated a $10 million advertising budget with Facebook while publicly questioning whether such ads could influence consumer behavior". Microsoft & Wine.com moved their entire display ad expenditure to other digital channels because of their concern that users clicking on display ads "may not convert to customers or sales," (Barr and Gupta, 2012).

Despite all these issues associated with the effectiveness of banner ads, they do perform, and they are unlikely to disappear anytime soon. Banner ads that are effective still deliver conversions and will remain part of the advertising mix of online advertisers. After declining for a few years, banner ads spending grew dramatically over the last few years on the back of newer forms of banner ads which combine latest technology to target the user better. Spends on banner ads is forecast to reach $158 billion worldwide in 2022 (Newor Media, 2022), an increase of 12.7% over 2021, and more than double the spend in 2017.

What has helped the resurgence of banner ads are advances in technology. Technology like programmatic advertising engines can now target audiences with pin-point accuracy to deliver relevant content that strikes a chord with consumers (Chen, 2020). Serving consumers with ads that resonates with their interests and behavior is more likely to elicit a click response from the user. This has resulted in a far more efficient usage of the banner ads.

Having said that, banner ads still lag behind other forms of digital advertising channels in terms of effectiveness. The topic of effectiveness of banner ads is an ongoing discussion (Sherman & Deighton, 2001; Mandel & Johnson, 2001; Li & Leckenby, 2004; Fang, et al., 2007; Todri, et al., 2019; Yuping, L-T. (2019). In an attempt to answer this question of effectiveness, a lot of effort has been directed towards understanding how best to target an ad placement so that it results in an alignment of users' interest & behaviour leading to a click response from the user. This is fine as long as a click is the ultimate objective of placing any ad. But the ultimate objective of placing any ad in any medium by any firm is not just to elicit a click response. Advertising on a digital channel allows advertisers to link exposures of ads to sales, a feature which according to Danaher and Dagger (2013), is not provided by traditional media. Hence, firms that pay for and place a banner ad, do so with the intention to draw the user to not only click on the ad but to complete an action on the website resulting in a sale/conversion. In this sequence of events leading to a sale/conversion, while the pre-click behaviour of users has been studied a lot, there is not much focus given to studying post-click behaviour which the authors of this paper believe could provide valuable insights which has the potential to further augment the effectiveness of banner ads. This brings out the necessity to develop methods which are reliable and that establish linkages between "Online display advertising and customer behavior".

One way to establish these linkages is to study the post click behavior of the users and factor that affect the chances of them completing a sale/conversion. As far as the post click behaviour of the user is concerned, when the user visits the website as a result of a click on a banner ad, it results in the user interacting with the brand on its website. Each of these interactions leads to dimensions of a) time spent, b) no. of pages browsed, c) depth of page in the structure of the website, d) whether this visit was the first visit or the second visit or the nth visit, e) the time since last visit, f) source of the media channel through which the customer arrived on this website, etc. All of these dimensions put together can be referred to as "depth of interaction". It can be argued that deeper the interaction, the more likely they are to move towards the final desired goal of taking action (sale/conversion).

This research paper's objective is to establish the impact of post click behaviour of the user on the sales/conversion process through the "depth of interaction". Such research is important to determine actions brands can take to increase the chances of converting a visitor to their website into a customer who completes the sales process by taking action i.e., buying the brand. Firms already invest a good amount of resource in understanding the pre-click behavior of users by way of placement & targeting. If depth of interaction has positive impact on the sales process in the digital display advertisement channel, brands can look for ways to increase the "depth of interaction" which will help them increase the conversion of visitors to customers. As such, this research hopes to provide a direct input into investment decisions brands take when planning an advertising campaign.

Review of Literature

As proposed by Mehrabian and Russell in 1974, the “Stimulus-Organism-Response (S-O-R)” theory forms the basis of this research study. The S-O-R model is a right fit for any research that aims to get an understanding of the different aspects of consumer behavior (Rodrıguez-Torrico et al., 2019; Kim & Lennon, 2013). According to Loureiro & Ribeiro, 2014 and Kamboj et al., 2018, the S-O-R theory is extensively used to study the “effect of online stimulus on consumer behavior”. The theory states that when consumer is exposed to a certain stimulus, it leads to a “cognitive and affective reaction (organism)”, which leads to a positive behavioral response (R).

In this study, digital display/banner ads by the marketers is the stimuli administered to the consumers, resulting in some of the users who click on the display ads and jump to the advertisers’ website. The users’ affective reaction on the advertisers’ website results in dimensions of a) time spent, no. of pages browsed, b) depth of website pages visited, c) no. of time visited, d) recency of visit, etc. which are all summed up as depth of interaction. All of these responses will eventually lead to behavioral change in the consumer in the form of buying the advertised products. These variables are further discussed below.

Effect of Display/Banner Advertising on Consumer Behavior

In their research, Auschaitrakul S. & Mukherjee A. (2017), found that “online display advertising is more effective in terms of attitudes toward the advertisement and brand when it appears on a commercial websites like an advertisers’ website as compared to social websites such as LinkedIn or Facebook”. It turns out that online banner advertising is more effective on a brands’ website as opposed to on individual pages on social media websites.

Research has proven that banner ads influence browsing behavior subsequent to a click for certain customers (Rutz, Bucklin, and Trusov, 2011). The effectiveness of an ad is impacted by the customer’s perceptions of the said ads’ informativeness and obtrusiveness (Bleier and Eisenbeiss, 2015). Studies to investigate the advertising impact of banner ads at various stages of the purchase funnel a.k.a. AIDA model have found that exposure of display ad has positive impact on later visits to the company’s website (Hoban and Bucklin, 2015). The effect of online display advertising on website traffic and brand awareness (Ilfeld and Winer, 2002), as well as effect of banner ads on awareness of the brand and ad recall (Dreze and Hussherr, 2003) have been studied in the past.

It’s clear from above that display banner ads do have positive affect on some aspects of user behavior. But advertisers have moved from traditional channels to digital channels not only because they are able to target customers more accurately, but also because digital media channels allow them to establish a link between clicks and ad exposures to sales, a feature Danaher and Dagger (2013) suggest cannot be provided by traditional media. The most convincing demonstration of the effectiveness of display advertising according to Sethuraman, Tellis, and Briesch (2011) is by linking such effort to sales/conversions. Assessing advertising effectiveness by linking clicks to sales can be done using two methods: field experiments and econometric models (Danaher, P. J., 2021).

Field Experiments

To determine ad effectiveness, field experiments were first used by Lambrecht and Tucker (2013), in their award-winning research publication in the Journal of Marketing Research. Retargeting customers who have already demonstrated product predilection, is more likely to result in a positive response. But this makes the ads appear more effective than it actually is and, according to them, they show as high as six times more sales. The researchers, therefore, created a treatment group and a control group and showed retargeted, product-specific ads to the treatment group and generic product category ads to the control group. The retargeted ads turned out to be less effective than the generic ads. Reason being that these customers were in different stages along the purchase funnel. While retargeted ads do work well at the end of the funnel when the user is near purchase, they are not effective for most customers who are starting on their search journey. This proves that users’ multiple interaction with the website (following a click on a banner ad) leads to consumers moving further along the purchase funnel leading ultimately to the end goal viz. sale/conversion. This has also been studied by other researchers using the Hidden Markov Model.

The usage of field experiments for determination of ad effectiveness has subsequently proliferated with studies done on Facebook (Gordon et al., 2019) and Google (Johnson, Lewis, and Nubbemeyer 2017) by creating randomized control groups. A field experiment by Sahni (2016) showed that digital ads for one restaurant led to an increase in sales at a competitor restaurant that offered similar cuisine. In all case where field experiments were done, it has shown that such experiments are not only difficult to setup but the effects of advertising are also difficult to detect. In the study by Gordon and colleagues (2019) of Facebook ads, they examined 15 different campaigns and discovered that just eight of these produced results that pointed to a statistically significant increase in sales.

Econometric Modelling

Users as individual customers have different ways to use the internet, and advertisers also deliver digital ads through unique ways. In such a situation, econometric models offer a flexible approach to gauge effectiveness of advertising. Econometric models can be used in examination of time series data, i.e., weekly, monthly, or annual records of sales and advertising. The effect of traditional and digital advertising on online sales and in-store sales was studied by Dinner, van Heerde, and Neslin (2014) for a premium clothing retailer over a period of 103 weeks. According to their finding, online paid and display ads were more effective compared to traditional forms of advertising. Even though firms have the expectation of advertising on digital medium influencing only online sales, according to the authors, it also ended up influencing sales inside the stores. Like Danaher and Dagger in 2013, econometric models can also be used to study single-source data which can link ad exposure at individual-level to sales.

Given that field experiments are difficult to setup and effects of advertising are always difficult to detect, it is the econometric approach to studying effectiveness of display banner ads, by linking clicks in display medium to sales, that the authors of this paper intend to explore. In order to link the clicks in display channel to sales, we need to understand the behavior of the user after clicking a banner ad and before completing the sale/conversion, to be referred as post click behavior. For this, we need to explore the AIDA funnel to identify stages a user will go through before they ultimately buy/convert to become a customer.

The AIDA Model

Since its introduction (Lewis, E. St. E., 1903) and mentions in the literature of marketing and advertising by Strong (1925), the AIDA model is one of the many models that measure and analyse customer journey from a complete stranger to the first point of contact with the brand to purchase. It belongs to the 'hierarchy of effects model' (Barry & Howards, 1990), which means that consumers go through various stages when making a purchase decision.

According to Lewis (1903) and Strong (1925), the stages, "Attention, Interest, Desire, and Action, form a hierarchy that is linear in nature. The AIDA model is based on the assumption that all buyers go through a cognitive and affective stage behaviour sequence (Vakratsas, D., & Ambler, T., 1999), which at the end culminates in a behavioral outcome which results in actual buying. Users move through the stages of the funnel in a sequential manner, moving from one state to another, till they are at the last state where they complete the task of buying/conversion.

Factors affecting subsequent behavior along AIDA Funnel

Dwell time or time spent on a website in a single session has been studied by many researchers and proven to have positive correlation with the expected response. Some researchers have studied dwell time with the aim to prove the effectiveness of information served in a document retrieval system (Yi et al., 2014; Liang et al., 2020; Ma et al., 2018; Wen, Yang & Estrin, 2019). While some researchers have studied dwell time with the aim to understand its direct impact on sales in online display advertising (Barbieri, Silvestri & Lalmas, 2016; Zhou et al., 2018; Kim et al., 2014; Lalmas et al., 2015).

Chatterjee, Hoffman, and Novak (2003), in their research found that "the customers' response to banner ads depend on the a) frequency, b) cumulative exposure, and c) elapsed time since the last click".

They found a non-linear relationship that was decreasing, much like a decay in value. Chances of customers clicking on the ad is less if the same banner ad is shown again and again to them. But those customers who visit after a longer time span are more likely to click than those who visit sooner. In other words, customers who are exposed to the display ad recently or are exposed less frequently are more likely to click. The impact of the exposure of display ad, beyond the CTR, has also been studied on purchase rate. Based on their study, Manchanda et al. (2006) showed that "the number of exposures to a banner ad accelerates a purchase". This impact increases as the customer frequents more websites. In addition, they found a direct relation between a greater number of exposures and more sites on which the banner ads are shown in comparison to the chances of repeating purchases.

Re-targeting technique is a far more recent trend in display advertising in which customers are exposed to ads of previously watched products. According to Goldfarb and Tucker (2011a), "the ad that is both obtrusive and targeted has less impact on purchase than ads that are either one". Goldfarb and Tucker (2011b), in another paper, again came up with the conclusion that the ad effectiveness is undermined when regulations restrict behavioral targeting.

From extant literature, demonstrated above, the following are some of the post-click factors that have a direct impact on the final sale/conversion.

1. time spent in a single session on the advertiser's website
2. no. of pages browsed in a single session on the advertiser's website
3. depth of pages browsed (as laid out) on the advertisers' website
4. no. of such sessions within the campaign period
5. recency of the current session compared to the last session

The above set of actions that arise as a result of users' actions on the website of the advertiser after clicking on the ad and before taking an action that counts as conversion is what the authors of this paper term as the depth of interaction. Beyond these factors, there are a few other factors that can possibly have an effect on the final sale/conversion. One such variable that may affect the dependent variable is the device on which the ad exposure takes place, and, therefore, also the device on which the visited session is browsed (Kaatz, Brock & Figura, 2019)

Extant research has studied the effect of ad exposure and click on the purchase/conversion. Extant research also shows investigation into product category, the spillover effect of previous visit to the current visit, frequency of ads exposure and the eventual click leading to a visit to the website. But there is no material on the effect depth of interaction (actions taken post the click) has on the final purchase/conversion. The authors of this paper, therefore, have set out to answer a simple question – do clicks that lead to a higher depth of interaction have a higher probability of conversion? Based on the review of existing literature on the subject and the discussion above, the authors have identified the following research gap.

Research Gap

Existing research in the field has thoroughly studied the effect of pre-click parameters on the final outcome (purchase/conversion) but there is no study on the effect of post click parameter (depth of interaction) on the final outcome (purchase/conversion) within the display medium. Previous studies suggest that higher the values of the variables #1, #2, #3, #4, #5 above, the higher the chances of conversion. But it is yet to be seen what effect they have on the final outcome if they are combined together.

Research Objective

This paper is investigating the role of depth of interaction post each click within the display advertising channel on the final outcome (conversion/no conversion). The final outcome is depicted as either a purchase/conversion or no purchase/conversion. The authors of this research paper intend to create a mathematical model that can predict the outcome (conversion/no conversion) of a digital display advertising campaign's exposure to a consumer by studying the effect of the various elements of the depth of interaction on the consumer's action.

If the final conversion is positively correlated to individual variables within the depth of interaction, it is likely that together, as depth of interaction, also they are positively correlated. Hence, the following hypothesis are proposed:

H1 = Final conversion is positively correlated to average duration (time spent).
H2 = Final conversion is positively correlated to average no. of pages browsed.
H3 = Final conversion is positively correlated to average depth of pages browsed.
H4 = Final conversion is positively correlated to recency of visit to the website.

Over years, with the rise of the mobile phone as a primary device to access the internet, it is shown to have a higher likelihood of results (conversion/no conversion) delivered during digital advertising campaigns. This leads the authors of this paper to propose the following hypothesis:

H5 = Final conversion is positively correlated to the device used during last visit to the website.

No other model previously constructed, predicting the effect of a click on the final outcome, has used depth of interaction as a critical variable for interactions through the digital display medium. It is the authors' contention that depth of interaction can better predict the probability of a click via digital display medium, leading to a positive outcome (conversion/no conversion). Hence, the authors propose the following hypothesis:

H6 = A model using depth of interaction can better predict the final outcome (conversion/no conversion).

Research Methodology

Data & Sampling

The research design used in this study is prescriptive design. Instead of studying how consumers will react when presented with the stimuli (digital display ads) by asking them before they are exposed to the stimuli, this paper studies how consumers reacted after they were exposed to the stimuli. Data considered for this study is post-stimuli action (as taken by the consumers when exposed to the ads). The different variables being considered in this study are all measured once the first action (clicking on an ad) has been taken.

The data for this study was taken from a digital display campaign of a credit card company which was running the campaign to induce consumers to click on the digital display advertising ads, land on the company website and fill a form in order to be called back by company representative who would help the consumer through the rest of the process of acquiring a credit card. Therefore, for the purpose of this paper, the act of filling the form and submitting it successfully constitutes a sale/conversion. Data considered is for a period of 31 days during the month of Jan & Feb 2022 (specifically 17th Jan 2022 to 16th Feb 2022), during which the company ran all its ads.

Sample Selection

A total of 12,378 unique consumers interacted with the advertising campaign during the said period (17th Jan 2022 to 16th Feb 2022). Of these, those whose series of exposure to the various ad within the campaign included at least one exposure to digital display (banner) ad was 2,784. In order to select purely random sample within the above group, random numbers were generated using www.randomiser.org. This selection was irrespective of whether the series of ad exposures to a consumer ended in a conversion or not.

Sample Size

Slovin's formula (Chakraborty & Bhat, 2018) states that the sample size for the study is 100.

Slovin's formula n=N/(1+N*E2)

Where "n" is the sample size, "N" is the population from which the sampling is done, and "e" the margin of error that is acceptable. The sample size chosen is likely to give 90% confidence in our estimates.

Since, target audience for the campaign is 15 million, the sample size was calculated to be 99 according to the above formula. While the sample size is 100 consumers, the amount of data generated by 100 consumers is voluminous on account of each consumer having gone through an average of 6 sessions in each customer journey. Each of these sessions, by themselves, generate considerable amount of data.

Analysis

According to IBM Analytics "Logistic regression is a multivariate technique used to classify a data into groups which is known by estimating the probability of an event occurring or nor not occurring, for example whether customers buy or don't buy, based on a set of the customers characteristics". Since, the value of outcome variable of a logit model is a probability between 0 and 1 we can decide the group of particular case by using a cutoff value. The logistic function, also known as logit function, is represented as below:

$$Logit\ (y) = 1/(1 + exp\ (-y)\ )$$
$$where\ \ y = \beta_0 + \beta_1 * x_1 + \ \dots\dots + \beta_n * x_p$$

Here logit(y) is the dependent or response variable while x is the independent variable. The analysis calculates the conditional probability for each observation. This value is logged and summed in order to find the predicted probability for each observation. For binary classification, a probability value of less than the cutoff value 0.5 will be classified as 0 while a probability value greater than 0.5 will be classified as 1. The model thus computed, is evaluated by applying on a test data set to find out the goodness of fit.

We build two models – one taking into account all the post-click variables and another without any of the post-click variables. In the second model, we assume a click to be a binary response to the stimuli i.e., the banner ad. The accuracy of the 2 models will demonstrate if depth of interaction is a better predictor of final sale/conversion.

Data Analysis & Interpretation

The data was analyzed using the SPSS software.

Table 1
Descriptive Statistics for the Scaled Variables

	N	Minimum	Maximum	Mean	Std. Deviation
Display	100	1	3	1.75	.744
Duration	100	29	1260	305.38	232.99
Pages	100	0	6	2.98	1.463
Depth	100	0	5	2.39	1.428
Recency	100	0	15	4.82	3.594
Valid N (listwise)	100				

Table 1 shows the descriptive statistics of the scaled variables. Display is the number of times a visitor clicks on the display Ad. The maximum is three times, the average is 1.75 which is close to 2. The Duration or the total time spent is minimum 29 seconds with maximum 1260 seconds average duration which is the time spent during each visit is 239.99 seconds which is about 4 minutes. While the maximum no. of Pages visited is 6 and the Depth of pages per visit is a maximum of 5 with an average of 2.39 which is close to 3. The maximum days since last visit, as denoted by Recency, is 15 days with an average of 4.82 days.

Table 2

Frequency for the Dependent Variable Of How Many Visitors Converted

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No-Conversion	52	52.0	52.0	52.0
	Conversion	48	48.0	48.0	100.0
	Total	100	100.0	100.0	

Table 2 above shows the frequency for the target or dependent variable where there are 52 visitors out of 100 who did not convert which is 52%, and only 48% of the visitors converted i.e., filled the form and submitted successfully.

Table 3

Frequency of the Device Used by the Visitor in Their Last Visit

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Mobile	57	57.0	57.0	57.0
	Laptop	43	43.0	43.0	100.0
	Total	100	100.0	100.0	

The table 3 above shows the *Device* used by visitors use during their last visit. We can see that majority of the visitors used Mobile (57%) and some used laptop (43%).

Table 4

Model Summary of Binary Logistic Regression

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	92.967[a]	.366	.488

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Table 5

Table of the Variables in the Model with Their Coefficients, P-Value And Exp. (B)

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Display	.298	.377	.623	1	.430	1.347
	Duration	.003	.002	4.934	1	.026	1.003
	Pages	-.265	.206	1.659	1	.198	.767
	Depth	.600	.232	6.688	1	.010	1.823
	Recency	.175	.080	4.806	1	.028	1.192
	Device_LastVisit	1.843	.568	10.511	1	.001	6.316
	Constant	-4.177	1.113	14.099	1	.000	.015

a. Variable(s) entered on step 1: Display, Duration, Pages, Depth, Recency, Device_LastVisit.

The table 5 above displays the regression coefficients, where *Duration*, *Page Depth*, *Recency* of visit, and the *Device* used in last visit are all significant variables in predicting the correct group in the target variable Page Event as the sig value of the these coefficients are less than .05. Only *Display* which is the number of time visited or frequency and no. of *Pages* visited doesn't seem to play a significant role in predicting the target variable group. The Cox and Snell R^2 is .366 and Nagelkerke R^2 is .488 which is fairly good. The overall model is good as the Nagelkerke R^2 maximum value is less than 1.0. The Exp. (B) value shows that except No. of *Pages* visited, all other variables are positively correlated with the dependent variable page event, as the value is greater than 1 for these variables.

In terms of the importance of the variables, the Wald statistics show that *Device* used during last visit (10.511), followed by *Depth* of pages visited (6.688), *Duration* of visit (4.934), *Recency* of visit (4.806), and finally no. of Pages visited in each visit (1.659) are important in decreasing order of importance.

The final model predicting the probability of a visitor converting, therefore, can be written as

$$\mathbf{y} = \mathbf{0.30} * \boldsymbol{Display}\ \textbf{click} + \mathbf{0.003} * \boldsymbol{Duration}\ \textbf{of visit} - \mathbf{0.27} * \boldsymbol{Pages}\ (\textbf{no.}) + \mathbf{0.60} * \boldsymbol{Depth}\ (\textbf{level}) + \mathbf{0.18} * \boldsymbol{Recency}\ (\textbf{days}) + \mathbf{1.84} * \boldsymbol{Device}\ (\textbf{Last visit}) - \mathbf{4.18}$$

With the above value of y, as observed for each visitor, the odds of a particular visitor converting (buying) is calculated using the logit function. Higher the odd, where max is 1, higher the chances of the visitor converting i.e. Page event becoming 1 which means they will convert.

Table 6a
Classification Table with Only Display As the Independent Variable

Observed			Predicted: Page_Event No-Conversion	Predicted: Page_Event Conversion	Percentage Correct
Step 1	Page_Event	No-Conversion	26	26	50.0
		Conversion	17	31	64.6
	Overall Percentage				57.0

a. The cut-off value is .500

Table 6b
Classification Table with All The Independent Variables in the Data Set

Observed			Predicted: Page_Event No-Conversion	Predicted: Page_Event Conversion	Percentage Correct
Step 1	Page_Event	No-Conversion	41	11	78.8
		Conversion	6	42	87.5
	Overall Percentage				83.0

a. The cut-off value is .500

The table 6a above shows the classification based on the derived model from the binary logistic regression when Display is the only independent variable taken into consideration i.e., post-click factors are not taken into account. The overall hit ratio is 57% meaning that the model categorises 57% of the original group correctly. The cut off chosen was 0.5, based on which the model gives individual classification of people who have converted (64.6%) and people who have not converted (50.0%).

The table 6b above shows the classification based on the derived model from the binary logistic regression when all the post-click independent variables in the study (constituting *depth of interaction*) are taken into account. The hit ratio here increases to 83% meaning that the model categorises 83% of the original group correctly. The cut off chosen was 0.5, based on which the model classifies people who have converted (87.5%) more accurately than people who have not converted (78.8%).

Discussion & Conclusion

In this paper, we modelled the likelihood of consumers converting at the end of a series of exposure to an ad campaign across various digital media channels, at least one of which is digital display banner ad. As shown in Table 5, we found that among the variables that constitute the depth of interaction, the following have an acceptable significance value (sig< 0.05) in predicting the target variable:

Duration of visit = 0.026 < 0.05
Depth of Pages = 0.010 < 0.05
Recency of Display = 0.028 < 0.05

Based on the above data, we are inclined to accept hypothesis H1, H3 & H4. The data also show that no. of Pages visited does not affect the final outcome of the customer's journey as shown by its significance value which is 0.198 (sig>0.05). Hence, we are forced to reject the hypotheses H2. The data also suggests that Device used has a significant effect on the final outcome of the customer journey, as shown by its significance value which is 0.001 (sig<0.05). Consequently, we accept the hypothesis H5.

The pseudo R2 values of Cox & Snell (36.6%) and Nagelkerke (48.8%) suggest a reasonably good model fit. More importantly, the Wald test shows that the variables contributing most to the final outcome, in the decreasing order of importance are Device used, Depth of pages visited, Duration of visit in a session and the Recency of visit.

The Exp (B) of the model shows that Duration, Depth, Recency & Device are the variables whose values are higher than 1 indicating that their increasing value corresponds to an increasing likelihood of positive outcome (conversion). The Exp (B) value of No. of Pages visited is less than 1 which indicates an increasing value will have a decreasing effect on the final outcome. This is confirmed by the fact that the B value of no. of Pages visited is negative (-0.265).

Along with all the above statistics, the derived model with all the independent variables of depth of interaction included (Table 6b) shows a prediction hit rate of 83% when the cut-off value is 0.5. The same model, including only the Display variable (without the rest of the independent variables – Table 6a) shows a prediction rate of 57% when cut-off value is 0.5. The result in Table 6a is to show results of final outcome when Display ad click is treated as binary (clicked – 1/Not clicked – 0). This is how researchers have treated the Display ad click variable so far. This paper, as was proposed at the beginning, looks beyond the binary value of the click and looks at subsequent actions taken by the user as having an effect on the final outcome.

There is a 45.6% jump in the accuracy of the model when independent variables representing depth of interaction are taken into account. This shows that the depth of interaction is better able to predict the final outcome as compared to just the click data. The authors of this paper, therefore, are inclined to accept the hypothesis H6.

It is noteworthy that earlier studies like Chatterjee, et al (2003) were not able to establish a correlation between various visits/sessions, this study is able to establish the significance of the recency of visit as a variable i.e., a click on the digital display ad later in the customer journey has a significant contribution to the final outcome. It is also important to note here the strong importance of device used in predicting the final outcome.

Contribution to Theory

This paper's contribution to theory is manifold – primary among them is the ability to look at all that happens after an ad has been clicked. Few researchers have attempted to observe the interaction that takes place once an ad is clicked and its effect on the final outcome. In that sense, the biggest achievement of this paper is to link advertising exposure, as determined through a click on the ad, to subsequent response of the consumer leading to the conversion, as determined by the depth of interaction. In the absence of this linkage, a click on an ad is considered a binary event, whereas this paper proves that the event has a value between 0 & 1 depending on the depth of interaction.

Managerial Implications

The biggest takeaway for managers, from this paper, is an understanding of how critical digital display advertising is to the success of an ad campaign as determined by the final outcome and not just ad exposure as determined by the click. Managers can now optimize their campaign budgets based on the subsequent action a customer takes post clicking on a display/banner ad (depth of interaction) rather than just the click on the ad (binary value 0/1).

It is established through this study that the device used to click and browse the website is the most significant to the final outcome, and therefore, managers need to ensure the content on their website as well as advertising creative/copy is designed to fit the device where the ad exposure takes place. In other words, different ad and content is required on different devices to persuade consumers.

This paper also establishes the importance of Depth of pages visited on the website as well as Duration of the visit and Recency of display. This means managers must plan their ad campaigns in such a way that there is good amount of spacing between one exposure and the next. At the same time, the content on the website should entice the users to spend more time and go to deeper level pages (e.g., category & product) rather than stay at the higher-level pages (e.g., homepage). The implications here, therefore, is not only for how an ad campaign is designed but also how the website which the customer visits should be designed. A few simple tweaks to the advertising creative and website content, keeping in mind the devices used to access the website, can potentially result in a better return on investment by making the ad campaign more efficient by delivering higher conversions.

Another important learning managers can take away from this study is the importance of digital display/banner ads in a campaign whose objective is conversion. It is widely accepted that digital display ads do a better job of building brand awareness and not necessarily a good job of conversions. According to the widely accepted view in the industry, among the digital media channels, search engine-based text ads (also known as pay-per-click ads) are more geared towards conversion. In case managers want to use the display advertising channel for conversion, this study provides a deeper understanding of what works and what doesn't in digital display campaign geared towards conversion.

Further, this study is not only critical for the advertisers, but for publishing companies too who depend on revenues from display advertising as well as the online companies that manage the sale and distribution of such display advertising. It gives them an idea about what would give the advertising companies who publish their ads on these platforms better returns on their investment. Giving better results to advertisers is a sure way to get them back repeatedly to advertise with them and thus increase their revenue.

Limitations & Future Scope

Like any other study, this study has its own share of limitations. These limitations also provide an opportunity for further research in this area. One of the most obvious limitations is that consumer profile data has not been looked at in this study i.e., the study treats a male and female consumer as same, a 15 yrs. old and a 35 yrs. old consumer as same, etc. Introducing the consumer profile data can bring out different results to the same study. It will be interesting to see how consumer responses differ on each of the demographic & geographic parameters.

The study also doesn't consider the effect of competitive brand activity on the consumers' click behaviour during the campaign. Another obvious shortcoming of the study is that it looks at digital display advertising in isolation, though in fact, in real life, consumers are exposed to ads through multiple channels in a single campaign. The dependent variable (the conversion in this case) is therefore, influenced by more than just one medium (in this case digital display channel). It would, therefore, be interesting to see the combined effect of multiple channels on the final conversion. Such a study is going to throw up a far more complicated model than the current one but is likely to be more insightful of how digital advertising works in real life i.e., in a multi-channel environment.

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