How much is enough? Determine the Optimal Frequency of Internet Display Advertising (IDA)

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by

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ABSTRACT

Half the money I spend on advertising is wasted; the trouble is I don't know which half"-

The words of John Wanamaker (1838-1922), a pioneer American marketer and advertiser, still hold true almost 100 years since they were spoken in the context of the ubiquitous banner advertising also termed as internet display advertising (IDA). Whilst IDA has become a major component of the internet advertising industry with an estimated size of US$ 56.5 billion (ZenithOptimedia, 2014) and a compounded annual growth rate of 21.5% (ZenithOptimedia, 2014), our understanding of how IDA works is fairly nascent. Despite thousands of advertisers utilising this platform to target billions of audiences worldwide, there is still a lack of clarity of how IDA really works. Specifically there is a gap in understanding the level of IDA impressions that are required to drive a specific goal. The blistering pace at which internet advertising has grown and evolved has contributed in a large part to a research gap that has stubbornly persisted. On one hand internet's constant evolution has spawned user journeys that are a complex tangle of advertising impressions, search clicks and website visits. On the other hand internet's exponential growth has led to constantly expanding data sets both

in terms of volume and number of variables. This has led to an ongoing need to constantly update the findings and methods in order to understand how IDA works. Developments in clickstream technology that track complex user behaviour on the internet have provided an opportunity to further research in the area of determining optimal frequency level in IDA to drive marketing goals.

This research seeks to assist researchers and practitioners in their quest to improve their understanding of IDA and internet advertising as a whole by uncovering a deeper understanding of the impact IDA impression frequency plays in driving marketing goals, especially online purchases. Further, the study analyses the moderating influence of consumers' characteristics and spacing of IDA impressions after controlling for a comprehensive set of factors related to media and seasonality. Lastly, the study uniquely utilises an easy to use but effective method that overcomes issues that plague clickstream data characterised by very large volume and low conversion rates. The clickstream data for this study was obtained from the ad-server log files from a large advertising agency based in Singapore. The use of such a data-set for this study is a significant step towards linking the world of information systems and marketing by making effective use of big data in developing optimal IDA impression frequency guidelines that will ultimately contribute towards improving the ROI of internet display advertising (IDA).

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INTRODUCTION

The quest to understand the effectiveness of advertising in driving marketing goals, especially purchases has endured ever since it was first famously encapsulated in John Wanamaker‘s famous quote, ‘Half the money I spend on advertising is wasted; the trouble is I don't know which half’. Despite the fact that a considerable amount of research has been conducted on the subject especially in the past 60 years, definitive answers to questions such as, ‘how much advertising is enough’, continue to evade researchers and practitioners alike. However, this situation is not due to a lack of effort. Indeed considerable research has been undertaken to determine optimal levels of advertising by determining the impact of advertising exposure frequency in driving marketing goals. The decades spanning 1960-2000 was a period of extensive research on the subject. Colin McDonald (1971; 1995; 1997), Michael J. Naples (1979; 1997), John Philip Jones (1995a; 1995b; 1997; 1998), Erwin Ephron (1995; 1997; 2005; 2006) and other researchers have made immense contributions to improve our understanding of what an optimal frequency level should be for advertising exposures. Since much of their studies were conducted to understand the impact of television advertising exposures on fast moving goods (FMG), large advertisers such as Unilever and Procter & Gamble benefited immensely from the findings of these researches.

Broadly, two opposing theories of advertising frequency got firmly established. ‘effective frequency’ or the ‘3 exposure theory’ got formal sanction after Naples’s (1979) seminal compilation of advertising exposure frequency studies done by researchers such as Zielske (1959), McDonald (1971) and others. Subsequently, the ‘recency’ theory or ‘one exposure is enough’ took root with the path-breaking work undertaken by Jones (1995a) titled, ‘When Ads Work: New Proof that Advertising Triggers Sales’, that deployed the new STAS technique which made use of single source consumer panel data. Both of these theories became immensely popular, and have endured to this day with many practitioners still deploying frequency setting rules that have emanated from one or both of the aforementioned frequency theories especially whilst planning for advertising on traditional advertising media.

However, as the environments and contexts under which the two frequency theories operate in, have undergone significant changes due to the advent of internet, many practitioners do not apply the aforesaid frequency setting rules while planning for internet advertising. By some estimates, 50% of practitioners do not use an advertising frequency rule of any sort while planning for internet display advertising (IDA), also known as banner advertising (Cheong et al, 2010). This undesirable situation has arisen despite the explosive growth of IDA ever since the appearance of the first internet banner advertisement in 1994. The lack of application of frequency rules to regulate and optimize the quantum of IDA exposures (or impressions) threatens to derail the blistering 20%+ growth in IDA whose current size already stands at US$56.5 billion (ZenithOptimedia, 2014).

The lack of appropriate frequency setting rules are a consequence of the limited research done in the area of understanding the impact frequency of IDA impressions has in driving specific marketing goals, especially when those goals are purchases. The reason for the paucity of research in this area is not due to the lack of trying, but rather due to IDA's growing size and complexity. Massive volume that runs into trillions of IDA impressions, fragmentation of these impressions across thousands of websites and the interplay of IDA with other forms of internet advertising such as paid search (Nottorf, 2013), are some of the issues which need to be grappled with. Moreover, the unavailability and inaccessibility of data that can trace every user's journey as it traverses scores of touch-points such as IDA impressions, search clicks, website visits and online purchases, has also contributed to the limited research in this field. Finally, the inadequacies of IDA metrics such as clicks and the preponderance of low conversion rates in IDA, has rendered the findings of many studies impractical for practitioners,

The good news is that recent developments in tracking technologies now allow third-party collection of granular user data that can trace a consumer's journey across multiple IDA impressions and other touch-points (Bucklin and Sismeiro, 2009; Nottorf, 2013). Therefore, the exclusive access to such a data-set from ad-server log files that comprises all IDA impressions for thirteen IDA campaigns of an integrated resort marketer based in South East Asia, provided a unique opportunity to undertake a study that sought to understand the impact of IDA impression frequency, possible.

This study analyzed the impact of varying levels of IDA impression frequency on online purchases by examining the differential impacts of IDA impression frequency levels across different consumer contexts such as consumers with high / low involvement and consumers with high / low brand familiarity. The study also examined the moderating impact of spacing between and across IDA impressions on IDA impression frequency's effectiveness in driving online purchases. The impact of frequency of IDA impressions on driving online purchases was measured after controlling for the effects of factors such as the quality of IDA impressions i.e. whether premium or mass, and seasonality i.e. festive or non-festive period.

A unique feature of this study is that it bridges the world of big data with the world of marketing. The access to a raw data set of the size which is approximately 256 GB and which consists of 770+ million impressions for 161+ million unique users is unprecedented. The data-set was corrected and checked for vexing issues such as 'non-viewable' IDA impressions and high 'cookie deletion' rates.

The analysis for the study involved tabulation of the data in a manner that overcame the issue of low conversion rates that characterizes much of internet advertising. The data was tabulated using the computational resources made available by Singapore Management University's HPCC servers. Thereafter the analysis utilized a unique polynomial model of the third degree in order to determine the level of frequency for IDA impressions that drove the highest online purchase conversion rates. The study also provides a stylized conversion revenue calculator for the benefit of practitioners in order to determine an optimal level of IDA impression frequency that can vary depending on whether the desired goal is to maximize conversion rates or profits.

Overall, this is a unique study that seeks to simultaneously plug the gap in IDA related research on one hand and to provide solutions for improving the internet advertising industry's performance on the other. It is hoped that this research will inspire more studies of this nature, especially as the world of internet advertising is expected to continually grow into the foreseeable future.

SIGNIFICANCE OF THE STUDY

The study is significant in that it provides contributions in many important areas and at many levels:

Impact on the industry

The study provides evidence of an optimal IDA impression frequency level at which online conversion rates are maximized. This optimal IDA impression frequency level varies by different consumer contexts such as high / low consumer involvement and high / low brand familiarity of a consumer. Moreover, the study provides useful guidelines on how to space IDA impression frequency. Thus these optimal frequency levels will be useful for practitioners whilst planning for IDA campaigns.

The study also differentiates between optimal frequency that maximizes conversion rates and that which maximizes profits. Depending on the IDA campaigns analyzed in the study, optimal frequency may be different or the same for conversion rate maximization or profit maximization. The impact of applying frequency guidelines on campaigns is significant. Based on the data-set of the campaigns analyzed, practitioners have a potential to increase online conversion revenue by up to US$ 2 million. These findings can be generalized for campaigns with similar specifications, and thereby potentially lead to a significant improvement in ROI of IDA. Given the size of the global IDA industry which is currently at US$ 56.5 billion (ZenithOptimedia, 2014), the improvement potential of IDA's return on investment (ROI) is tremendous and can have a significant positive impact on the industry.

Impact in the research field

The number of researches that measure the impact of IDA on purchases is limited. Therefore this study adds to the corpus of learnings that shows the impact of IDA in driving online purchases. Moreover, by also demonstrating the effect of IDA in driving attitudinal metrics as manifested by visits to websites, this research uniquely provides evidence and a valuable comparison between the effect of IDA on both purchases and attitudes in one single study with the same data-set.

Furthermore, this is perhaps one of the first studies that provides learnings on the differences in ad-response curves to varying levels of IDA impression frequency for different consumer contexts. This study also provides direction for future researches on probing the interaction effects between various consumer contexts and spacing of IDA impressions.

Finally, this research also provides a useful methodology to tabulate large data sets from big data for the task of understanding the impact of IDA impression frequency on marketing goals. Simultaneously, it provides an alternative model to analyze IDA impression given the issues of low conversion rates that characterize internet advertising's clickstream data.

Impact in the practitioner world

The study provides a link to frequency setting concepts such as ‘effective frequency’ and ‘recency’ that are more familiar to practitioners. This will hopefully pave the way for easier adoption of this study’s learnings in the internet advertising industry. As the analysis is done with campaign level data, the guidelines provide an approach to planning and buying for IDA that is practically feasible. This is significant given that frequency setting can currently only be applied for individual users, i.e., cookies, at a campaign level.

Impact on integration between the disciplines of marketing and information systems

The use of a big data set of such a magnitude is quite unprecedented. The approach used for this study provides useful directions for future researchers and practitioners seeking to integrate and leverage the mutually beneficial worlds of marketing and information systems.

Additionally, as a consequence of this study, four re-usable software codes have been developed using ‘R’ to extract, prepare and tabulate raw data from Double Click ad-server log files. Also, a useful code has been written to detect ‘non-viewable’ IDA impressions, a useful improvement in identifying the vexing issue of IDA impression viewability.

BACKGROUND

About Internet Display Advertising (IDA)

The growth of the internet, and its widespread adoption by consumers has naturally led to the rise of internet advertising. Amongst all the different advertising platforms available on the internet, internet display advertising (IDA) is one of the largest. The explosive growth of IDA has been well documented (Chatterjee et al, 2003; Manchanda et al, 2006; Braun and Moe, 2011; Danaher et al, 2014). From being the very first form of internet advertising way back in 1994 (Hollis, 2005; Aksakalli, 2012), to currently being an estimated US$ 56.5 billion dollar business (ZenithOptimedia, 2014), IDA has indeed come a long way. IDA now accounts for 42.8% of the total annual estimated internet advertising spends of US$ 121 billion. This makes it the second largest internet advertising format in terms of share (Li, 2011; Moon and Kwon, 2011; IAB 2013). IDA is expected to grow by 21.5% in 2015 and touch US$ 68.7 billion by 2015 (ZenithOptimedia, 2014).

Campbell et al (2014) have defined IDA as a “brand or product related content created by a brand and that runs distinct from editorial content” and for which “payment for time and space is made.” IDA consists of banner advertisements that are placed on third-party publisher (hereafter termed as publisher) websites on behalf of the advertiser, and for which the publisher charges a fee from the advertiser. An IDA banner advertisement is composed of an advertising message that is usually contained in a rectangular space that occupies about 10% to 15% of a website's page (Flores et al, 2014). Most IDA banner advertisements have internal links that connect them with other websites, which usually are the advertisers' own websites (Manchanda at el, 2006). An important point to be stressed is that IDA is not simply a listing of product or brand content on a brand's own website, or on a publisher's website, but a deliberate placement of a product or brand message on a publisher website. Publisher websites where IDA impressions can appear include large internet portals such as Yahoo!, social media sites such as Facebook, and special interest websites such as TripAdvisor. In addition IDA impressions can appear on thousands of smaller websites through advertising networks that consolidate and sell IDA impressions on behalf of the smaller websites.

IDA has many different banner advertising formats. Internet Advertising Bureau (IAB) has provided guidelines in order to standardise the various formats and sizes that should be used by the industry. The size of IDA advertisements are represented by the number of pixels contained within the banner and are usually represented by number of pixels that are present horizontally and vertically. For example an IDA format, 728 x 90, represents a banner advertisement which has 728 pixels horizontally and 90 pixels vertically. Among the most popular IDA formats are the 728 x 90 (termed as the leader board), 300 x 250 (termed as medium rectangle) and 160 x 600 (termed as wide skyscraper). Examples of some IDA formats are provided below (Image 1 and Image 2):

Image 1: Sample IDA

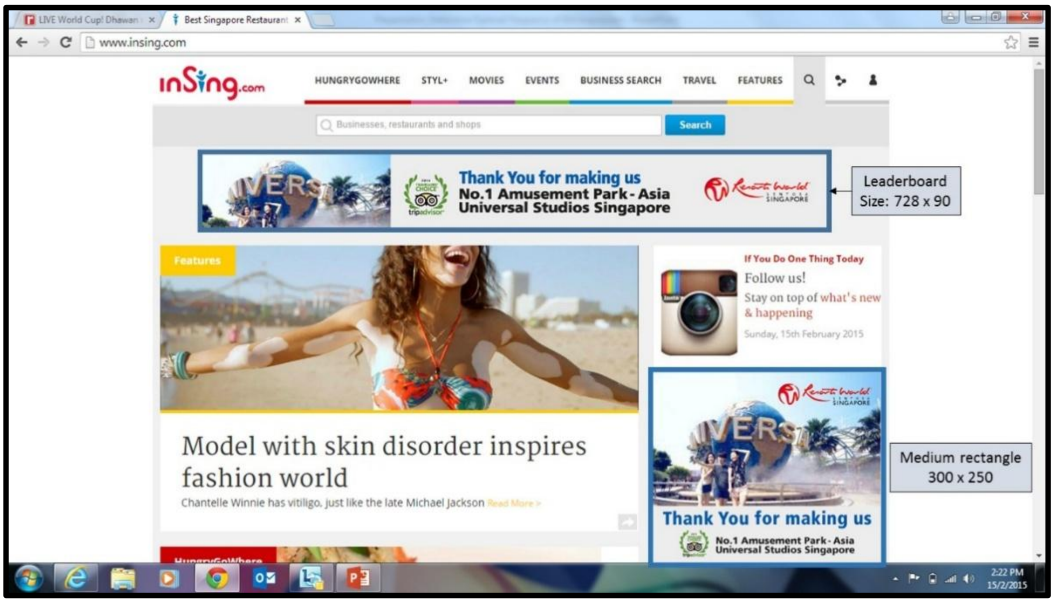
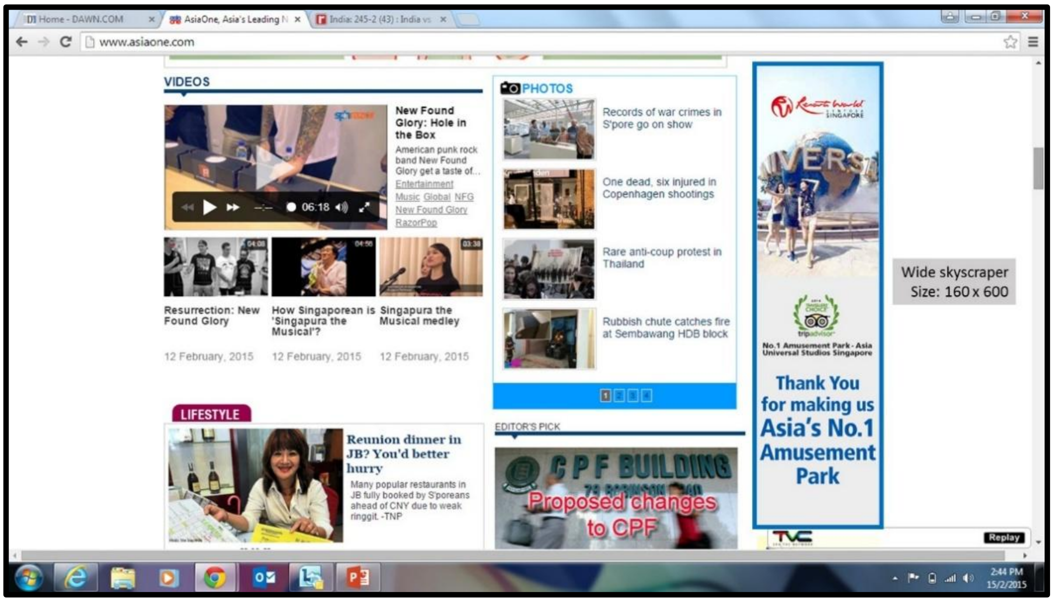


Image 2: Sample IDA



Measurement of IDA

The key metric for the measurement of IDA is an **impression**. An impression is defined as the publisher or a third-party ad server initiated loading of an IDA banner advertisement when an internet user visits a publisher website that has been contracted by the advertiser to display IDA advertisements on its behalf (Aksakalli, 2012). The loading of an IDA advertisement is termed as 'serving of an impression'. An important implication for IDA is that the number of advertisement placements displayed to users can be controlled by the advertiser (Chatterjee et al, 2003) provided the advertiser makes use of a third-party ad server (Danaher et al, 2014). This means that an advertiser can regulate the frequency of advertising exposures i.e. impressions and the timing of those impressions. Such advertiser control is not possible in case of paid search advertising where the timing and nature of the advertisement is controlled largely by the user. In the case of paid search advertising the control of the advertising exposure is in the hands of the user as the advertisements displayed are directly the result of keywords searched for by the user (Danaher et al, 2014).

The most commonly used metric to buy and sell IDA impressions is CPM (Moon and Kwon, 2011; Danaher et al, 2014). CPM stands for cost per mille (mille is the Latin word for thousand). CPM is the price charged by a publisher for every 1000 impressions that the publisher serves to users on behalf of advertisers (Danaher et al, 2014). Publishers are contracted by advertisers to serve a specific number of impressions for an advertising campaign for which the advertiser negotiates a CPM rate with the publisher.

CPMs of IDA impressions are usually very low as a result of which IDA in many instances costs lesser than exposures on traditional media advertising (Flores at al, 2014). For example an average CPM for a standard banner in USA in 2010 was US $2.52 (ComScore, 2010). Table 1 has a list of average CPM prices for IDA for some key categories of websites. Even in an expensive market such as South Korea the corresponding figure is only US$ 8.00 (Danaher et al, 2014). As a result of such low CPMs, an advertiser typically buys millions of IDA impressions in any one campaign.

Table 1: Top Display Advertising Sites, April 2010. Total US – Home and Work locations. Source: comScore Ad Metrix

Publisher	Total Display Ad Impressions (MM)	Share of Impressions	Estimated Spending ($ 000)	Cost per Thousand Impressions (CPM)
Total Internet : Total Audience	**354,636**	**100.0%**	**893,681**	**$2.52**
Social Networking	98,176	27.7%	54,684	$0.56
Portals	69,664	19.6%	181,266	$2.60
Entertainment	38,104	10.7%	181,147	$4.75
e-mail	34,327	9.7%	32,370	$0.94
Community	15,884	4.5%	33,435	$2.10
General News	12,542	3.5%	77,055	$6.14
Sports	10,850	3.1%	68,214	$6.29
Newspapers	8,506	2.4%	59,441	$6.99
Online Gaming	7,929	2.2%	21,234	$2.68
Photos	7,391	2.1%	7,953	$1.08

With advertising budgets for many advertisers being in millions of dollars, the sheer number of IDA impressions being served is immense. By one estimate, the number of IDA impressions that was served to users in USA in 2012 was 5.3 trillion (ComScore, 2013). Even in a small market such as Singapore, an advertiser with a modest advertising budget of US $100,000, can buy approximately 20 million IDA impressions based on a CPM of US$ 5.0. This price is calculated by assuming a 50% discount on the rate card price indicated on the website of a large Singapore based publisher, The Asiaone Network (2014). As a result, in a single advertising campaign the number of impressions that can be served per single user is extremely high (Nottorf, 2013). For instance, in the aforementioned example of a Singapore-based advertiser, 20 million IDA impressions would potentially result in an average of five impressions per user even if the advertiser were able to target every single internet user residing in Singapore which is estimated to be approximately four million users (Internet World Stats, 2013). Over the years, this large number of impressions being served has raised concerns about the effectiveness of IDA and as a result has led to a flurry of researches seeking to understand the impact of IDA impressions in driving advertising and marketing goals.

Need to determine the optimal IDA impression frequency level

Given the huge numbers of IDA impressions bought with an equally large amount of advertising dollars, the need for practitioners to determine an optimal level of impressions per user to drive marketing goals has become more acute. There is a need to get a deeper understanding of how frequency of IDA impressions really works (Chatterjee et al, 2003). Distribution of impressions can vary widely with some users being under exposed with few or no impressions whilst others being over exposed with very high number of impressions (Danaher et al, 2014). These variations in distribution of impressions raises critical questions that media planning practitioners need answers to especially with regards to understanding the impact of frequency of IDA impressions. How do consumers respond to different frequency levels of IDA impressions? Do different consumers respond differently? What are the factors which influence the impact of varying frequency levels of IDA impressions? At what frequency level of IDA impressions will the goals be maximised? Clearly, an understanding of the impact of IDA impressions at each frequency level across different consumer types or contexts is essential.

Not surprisingly practitioners such as Brunner and Gluck (2006), have listed the development of optimal frequency guidelines as one of the ten most important principles of media planning in the context of IDA. Huang and Lin (2006) in their literature review concluded that ultimately frequency of exposures, i.e. impressions, is a pre-requisite that drives advertising’s goals whether they are attitudinal or behavioural. Given the large size of the IDA industry and the criticality of determining the effectiveness of IDA impressions in driving marketing goals, the issue of determining the optimal frequency of IDA impressions is a significant one. With the availability of more in-depth and granular internet advertising clickstream data there is an opportunity to improve our understanding of the impact of frequency level of IDA impressions in driving marketing goals and thereafter determining the optimal level of IDA impression frequency (Bucklin and Sismeiro, 2009).

Some researchers have outlined the steps required to develop optimal frequency guidelines for advertising exposures. Cannon and Riordian (1994) have described a four-step process to develop an optimal frequency schedule for television which consisted of, 1) determining the advertising response curve, 2) determining the expected value of the schedule, 3) determining the exposure frequency distribution, and 4) calculating the value at each frequency level. Pepeljnak and Song (2003) proposed a similar three-step process for IDA which was, 1) to develop a response curve for every incremental IDA impression, 2) to calculate the cost for every incremental IDA impression and the revenue for every incremental response, and 3) to continue adding to the frequency level till profits are maximized. These guidelines were provided regardless of the metric the frequency of impressions was being measured against.

Based on the suggestions of these researchers, the following three steps were undertaken for this study with the objective of determining the optimal level of IDA impression frequency. The first step was to determine a metric for which IDA's effectiveness was to be measured against. The second step was to develop an advertising response curve that measured the impact of varying frequencies of IDA impressions on purchases. The third step was to determine the optimal level of IDA impression frequency that was required to maximize the metric that was identified in step one.

The following section summarizes the current researches on IDA that have focused on the aforementioned sub-fields. The objective was to understand the work already done and then to identify the gaps in the research which need to be filled.

CURRENT RESEARCH AND RESEARCH GAP

Researches to measure IDA's effectiveness

Output-based metrics i.e. clicks

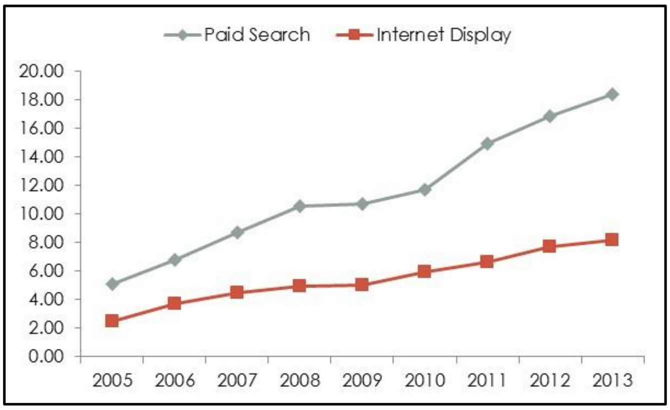
Much of the initial research into understanding IDA's effectiveness has been inadequate to increase our understanding of IDA's effectiveness. The reason which has now become the cause of a growing cynicism towards IDA, lies ironically in the very reason that contributed to the early growth of IDA. During the initial years of IDA, advertisers were excited about the interactive nature of the internet (Bezjian-Avery et al, 1998; Yoon and Kim, 2001) and the promise that it could elicit immediate responses from consumers (Fulgoni, 2013). This also drove the expectation amongst advertisers that IDA was more accountable than traditional media since the effect of every IDA impression (as measured by a click) could be tracked (Pergelova et al, 2010). Since a click was the primary response mechanism to an IDA impression, click through rate (CTR) became a popular measure to gauge the effectiveness of IDA impressions (Leckenby and Hong, 1998; Shen 2002; Fulgoni and Morn 2009; Fulgoni 2013).

Click is the number of times a user 'clicks' on an IDA banner advertisement. A click usually takes a user to another website, which is usually the advertiser's website, via a link. At times a user may close the link even before it fully loads onto the computer screen. **Click through rate (CTR)** is the "ratio of the number of times an internet banner advertisement (impression) is clicked, to the number of internet advertisements (impressions) that are served" (Aksakalli, 2012). It is expressed in percentage terms. In other words, CTR = Clicks/Impressions x 100. A related metric is **CPC (Cost per click)** which is the price charged by a publisher for every click that the publisher is able to generate (Moon and Kwon, 2011). In other words, CPC = Clicks/Cost of impressions. It is used to buy and sell both paid search advertising and IDA though the trend of using CPC to transact IDA has fallen out of favor with publishers due to declining CTRs (Shen, 2002).

Due to the early promise represented by the click a number of studies were carried out with the aim of improving CTRs. These researches focused on understanding factors that potentially drove higher CTRs such as understanding the efficacy of various advertising formats (Burns and Lutz, 2006; Sigel et al, 2008), advertising format sizes (Chandon et al, 2003), advertising creative messages (Meyer et al, 2011), impression exposure rates (Chatterjee et al, 2003 and interaction with other media (Nottorf, 2013). Despite a plethora of such researches, CTRs of IDA impressions have continued to decline over the years (Bucklin and Sismeiro, 2009) and by some recent estimates have dropped to below 0.1% (Fulgoni and Morn, 2009; Zorn et al, 2012). In fact some researchers had predicted a continuing decline in CTRs fairly early on. They postulated that as consumers' understanding of the medium improves, they would progressively have a better sense of which impressions to click on and which ones not to (Chatterjee et al, 2003). Despite this negative prognosis, advertisers and their media planning agencies have continued to plough millions of additional impressions in their zeal to drive up click numbers. However, even this is proving to be an exercise in futility as research has shown that the probability of a CTR tends to be lower when the number of IDA impressions is higher (Gopal et al, 2011). Even more damning is the evidence that clicks and therefore CTRs have no relation to marketer's end goals such as driving attitudes or behaviours (Dreze and Hussherr, 2003; Manchanda et al, 2006; Fulgoni, 2013; Fulgoni and Lipsman, 2014). Dalessandro et al's (2012) findings from 58 large-scale experiments showed that CTR was a poor proxy for predicting conversions and could even be misleading. The authors went on to say that "clicks... are no better than randomly guessing in a surprisingly large number of campaigns."

Clearly, the apparent failure of click as a metric to adequately measure and plan IDA effectively has been one of the primary reasons for the erosion of IDA's popularity amongst advertisers. Despite IDA being the first advertising platform on the internet, the gap in advertising spends between IDA and paid search advertising has widened with paid search advertising now being almost twice the size of IDA (Table 2) (PWC, 2005; 2006; 2007; 2008; 2009; 2010; 2011; 2012; 2013). This is due to the fact that whilst responses to paid search advertising have been shown to positively correlate with advertisers' advertising and marketing goals, the same cannot be said for IDA.

Table 2: Trends in advertising spends on paid search and IDA from 2005 to 2013



Fulgoni (2013) emphasised this point in his quote that “the click might reflect a consumer’s immediate reaction to an advertisement, but it ignores the impact of frequency of exposures.” Given the ineffectiveness of clicks, as a metric, researchers turned to measuring IDA’s effectiveness against attitudinal metrics.

Attitude based metrics

The failure of clicks and CTRs to truly measure the effectiveness of IDA impressions, brought forth the realisation that IDA didn’t work as an instant response platform. Rather research suggested that IDA worked in similar ways as advertising in traditional media in influencing attitudinal and behavioural metrics even without a click. One line of researches suggested that IDA impressions were effective even without a click and drove attitudinal measures such as advertising recall, attitude towards the advertisement, brand awareness, brand recognition, brand recall and purchase intent. A number of these researches were experimental in nature. A study by Cho et al (2001) using a proprietary ‘Cold Fusion’ technique showed that IDA impressions drove favourable attitude towards the brand and its advertisement as well as higher purchase intention of the brand. Dreze and Hussherr (2003) used eye tracking technology to show that multiple exposures of IDA impressions drove aided brand awareness, aided brand recall and unaided advertising recall. Yoo (2009) compared the impact of various IDA formats and showed that all the tested formats led to a more favourable attitude towards the brand, a greater brand recall and a higher intention to click. Lee and Cho (2010) through a controlled experimental study demonstrated the effectiveness of higher frequency of IDA impressions in driving attitudinal metrics such as ad recall, ad recognition, attitude toward brand and trial intention. Similarly another controlled experiment showed that IDA impressions led to higher brand recall and intention to click (Yaveroglu and Donthu, 2008).

Proprietary field researches conducted by advertising and research companies too confirmed the findings of the experimental studies. An Ogilvy Advertising study demonstrated that IDA impressions were effective in driving response based metrics from a direct response campaign and attitudinal metrics from a branding campaign (Broussard, 2000). A Millward Brown study showed that even a single IDA impression led to an uplift of brand awareness and brand loyalty even without a click (Briggs and Hollis, 1997). Another Millward Brown meta-analysis study demonstrated that a single IDA impression caused a 4% uplift in purchase consideration whilst 10 or more IDA impressions caused an 8% uplift in purchase consideration (Hollis, 2005). Havlena and Graham (2004) used sample data from Dynamic Logic's MarketNorm data-base to show that frequency of IDA impressions had a positive relationship with certain brand metrics for certain product categories such as brand favorability for FMG category, and purchase intent for automobile category. An analysis of 34 campaigns that ran in US and Europe showed that IDA impressions drove aided brand awareness, though the results were significant only for six of those campaigns (Lee and Briley, 2005). Whilst these studies were useful in quelling the notion that IDA was only meant to drive immediate responses such as clicks, and instead could play a role in driving attitudinal goals, these studies had limitations due to their experimental or proprietary nature and the fact that exposure and brand metric data were from different sources which caused potential misalignment issues.

The shortcomings of the aforementioned studies has led to a new line of researches that make use of internet advertising clickstream data to track consumers' behavioral responses to IDA impressions with or without a click. Bucklin and Sismeiro (2009) have defined clickstream data "as the electronic record of internet usage data collected by web servers or third-party services." Such studies have become popular at least in part due to the understanding that attitudes can be manifested in behaviors such as visits to websites. A study showed that IDA impressions drive traffic to a brand's website which in turn drives brand equity (Ilfeld and Winer, 2002). An analysis based on 139 separate studies showed that IDA impressions helped uplift traffic to websites by an average of 65% after one week of exposure (Fulgoni and Morn, 2009). The effect was the highest for the automotive category followed by retail & apparel, media & entertainment and electronics & software categories. A study that evaluated the impact of multiple media in driving purchases to an Australian departmental store showed that IDA helped drive traffic to the store's website (Danaher and Dagger, 2013). Another research showed that not only did IDA impressions influence own brand searches, but they also triggered competitive brand searches (Lewis and Nguyen, 2012). Kireyev et al (2013) showed that IDA impressions significantly increased search conversions as well as search clicks for a bank's checking account. Specifically the research showed that for every $1 invested in IDA impressions led to a return of $1.24 for IDA and $1.75 for paid search advertisements. Fulgoni and Morn (2013) concluded that IDA helps to build brand equity and preference which eventually leads to a purchase. They summed it aptly in the quote based on an earlier research (Fulgoni and Morn, 2009), "display builds the equity that search converts into sale."

Purchase metrics

Perhaps the most encouraging proof for researchers and practitioners that IDA is effective in driving marketing goals is seen in its influence in driving purchases. The growth of e-commerce has provided a direct linkage between the impact of IDA impressions and online purchases that can be tracked through clickstream data. Studies have shown that not only do IDA impressions drive website visits, they also drive online purchases. Manchanda et al (2006) demonstrated that a significantly higher proportion of online purchases was driven directly by exposures to IDA impressions (14.5%) than those driven by clicked IDA impressions (0.25%). However the limitation of the study was that it only measured the effects of IDA impressions on repeat purchasers. A study by Breuer et al (2011) showed that IDA worked both at a short-term level as well as on a long-term level to drive sales for an online book-store. However, the research measured only those sales that were attributed to clicked IDA impressions and not to non-clicked IDA impressions. A recent study using single-source (STAS) data revealed that IDA impressions drove short term sales in the FMG category in similar ways as television advertising though the effect was smaller and less consistent than that of television (Taylor et al, 2013). However, due to paucity of data the findings were not definitive. Danaher and Dagger's (2013) multi-media study showed that IDA impressions did not drive sales to an offline retail store possibly due to incongruency of the exposure media (which was online) to the purchase platform (which was offline). This alludes to the possibility that IDA impressions may have more discernible impact in driving online purchases rather than offline purchases. Finally, a recent study by (Johnson et al, 2014) has showed that IDA impressions drove offline purchases and that the effect of IDA impressions was more pronounced amongst those users who resided closer to the physical stores than those who resided further away. While this study had a large sample size of 20 million IDA impressions served to slightly more than 3 million users, it measured the impact of IDA impressions that appeared solely on one publisher website which was Yahoo!. This was perhaps not so surprising since the study was undertaken on behalf of Yahoo!.

In sum, whilst researches that have measured the effectiveness of IDA impressions in driving online purchases have provided invaluable evidence that IDA is indeed effective in driving marketing goals, the number of such researches has been rather limited. Therefore any further research in determining IDA's effectiveness in driving online purchases will go a long way in strengthening IDA's credibility amongst practitioners. Fortunately such researches are now feasible in large part due to improvements in clickstream data thanks to advancements in tracking technology. As a result the tracking technology now available enables the recording of all the instances of an internet user's exposure to an IDA impression, visit to a website, and an online purchase on an e-commerce platform even without a click occurring (Abhishek et al, 2013).

Researches to determine advertising response curves to frequency of IDA impressions

Broussard's (2000) research demonstrated that the advertising response curves for IDA impressions for two distinctive types of campaigns, a direct response campaign and a branding campaign, were different. The study showed that the direct response campaign had a sharply diminishing response curve after three impressions, and therefore a frequency level of three was recommended as being the most effective. In the case of the brand campaign, the advertising response curve was gradually diminishing and plateaued off at a relatively higher frequency level of seven. However, the metrics employed in the study, i.e. clicks in the case of the direct response campaign, and survey based brand recall in case of the brand campaign, were both fraught with issues that have been highlighted earlier.

Chatterjee et al's (2003) study was perhaps the first comprehensive study that used clickstream data to model the response of users to IDA impressions. The research revealed that the overall response (measured as a click) to repeated IDA impressions was diminishing in nature. The study also highlighted differences across two categories of internet users. Those who were exposed to a high number of repeated impressions within a session (referred to as high involvement users) had a steeper diminishing advertising response curve compared to those who had repeated exposures that were spread across many sessions (referred to as new or less frequent users). However, as the analysis used clicks as responses, the findings of the study have limited utility in relation to the objectives of our study.

Havlena and Graham (2004) provided some evidence that advertising response curves for IDA impressions were steeply diminishing and the effects did not last for more than a day for two product categories i.e., automobiles and pharmaceuticals. Hollis's (2005) meta-analysis using Millward Brown's extensive data-base of studies to gauge the effectiveness of IDA impressions demonstrated a diminishing advertising response curve for IDA impressions. The studies showed that a single IDA impression caused a 4% uplift in purchase consideration whilst ten or more IDA impressions caused an 8% uplift in purchase consideration. A study undertaken by Lee and Briley (2005) that analyzed message recall for 26,258 respondents across 34 campaigns in US and Europe used a binary logistic regression transformed model to gauge the frequency level of IDA impressions that drove the highest message recall. The results revealed an inverted 'U-shaped' advertising response curve with the message recall peaking at a frequency of close to seven impressions. The study used age and gender as control variables, variables that were obtained via an online survey. They found that over multiple impressions, recall was higher amongst women than amongst men. Similarly the recall was higher amongst people from the younger age group than from the older age group. However, much of the findings were not significant.

Manchanda et al (2006) provided evidence that a frequency of IDA impressions served over a week positively impacted online purchases, and the returns to each cumulative impression was diminishing up to the third impression. The study also showed that the impact of three IDA impressions across three websites was better than the impact of all three impressions on the same website, thereby suggesting that the number of websites had an influence on the shape of the advertising response curve. Their study also demonstrated that a fewer number of advertising creatives were more effective (versus a larger number) in driving online purchases.

Braun and Moe (2011), too used clickstream data to understand the impact of IDA impressions in driving conversions for an automobile firm. Conversions consisted of a broad list of specific activities undertaken by a user on the automobile firm's website and included actions such as a dealer location search, inventory search and receipt of quotations amongst others. The model assumed a diminishing response curve which was moderated by differences in advertising creatives.

Taylor et al's (2013) analysis of single-source data suggested a non-diminishing advertising response curve for IDA impressions compared to television impressions. This was based on the evidence that the average frequency that drove sales was higher for IDA impressions (average frequency = 11) than for television impressions (average frequency = 3.4). However, the authors questioned the results of the findings of this study by raising the issue of possible confounds such as advertising creatives and consumer loyalty. Therefore the findings have limited applicability due to the limited amount of data that could measure the effectiveness of IDA impressions.

Nottorf (2013) alluded to the existence of a diminishing advertising response curve when he modeled the effect of IDA impressions to clicks. The study factored in the impact of search on IDA impressions, as well as the impact of different media vehicles used for IDA – standard large portals such as Yahoo!, video sites such as YouTube and retargeting sites. The effects were noticeable for impressions on Yahoo! and retargeting sites, but not for YouTube. However, the research was based on clicks and thus cannot be directly applied to online purchases. Danaher et al (2014) modified an existing MNBD method to arrive at quick estimates of advertising response curves that were close to the enumerated advertising response curves which were diminishing in nature. However, as the advertising response metric was reach, the findings have limited applicability for studies seeking to determine the advertising response curves for online purchases.

The studies mentioned above, especially those conducted prior to 2010, whilst being extremely relevant at the time when they were undertaken, lack relevance in today's internet advertising scenario. Given the rapid development and expansion of IDA over the past fifteen years which has led to a proliferation of websites, increase in advertising clutter, emergence of a variety of advertising formats and more complex user behaviour, the findings may no longer be applicable in a majority of cases. Chatterjee et al (2003) stressed that internet based research should be refreshed every five years due to speed of change that the medium undergoes. Other researchers have also acknowledged the need to incorporate other controlling factors such as the type of publisher websites and consumer characteristics in order to develop a better understanding of the effectiveness of IDA impressions (Taylor et al, 2013). In conclusion, despite a fair number of studies that have analyzed advertising response curves for IDA impressions, there has been no research that has been specifically undertaken to determine the frequency level of IDA impressions that is effective in driving purchases whilst simultaneously incorporating factors that can possibly moderate the effect of various frequency exposure levels.

In sum, the literature on understanding the advertising response curves of IDA impressions in the context of online purchases is rather limited. The reasons for that are broadly due to, a) the lack of external validity due to the experimental nature of some studies (Dreze and Hussherr, 2003; Yaveroglu and Donthu, 2008; Lee and Cho, 2010), b) the limited generalizability of the findings of some field studies due to inadequate or insufficient data (Taylor et al, 2013; Danaher and Dagger, 2013), c) restrictions on wider application on account of their proprietary nature (Briggs and Hollis, 1997; Broussard, 2000; Chandler-Pepelnjak and Song, 2003; Hollis, 2005), and d) the focus on metrics other than online purchases, such as clicks (Chatterjee et al, 2003; Nottorf, 2013), reach (Danaher et al, 2014) and other website activities which are non-purchase related (Braun and Moe, 2011).

Research on IDA returns maximization

Studies that have analysed profit maximisation in the context of IDA have tended to be separate from those that have studied the impact of IDA impression frequency. Many of these studies have focused on developing guidelines for marketers in setting optimal budgets across different media (Naik and Peters, 2009; Pergelova et al, 2010; Wiesel et al, 2011; Danaher and Dagger, 2013).

Naik and Peters (2009) used a hierarchical model that incorporated within-media and cross-media synergies in order to recommend an advertising budget for a German car manufacturer that could maximise profits. Based on their model, the authors recommended doubling the share of IDA in the media mix compared to other media in order to improve profitability. Naik and Peters (2009) developed a new model (cross-media synergy principal component model) of budget allocation across internet advertising that took into account inter-media synergies, i.e. traditional media with internet media, as well as intra-media synergies, i.e. within traditional media. Pergelova et al (2010) showed in their study of the Spanish car industry that the efficiency of advertising improved for those car manufacturers who had included internet advertising into their media mix compared to those who had not. The study used a two-stage process that first used an output oriented Data Envelopment Analysis (DEA) to develop efficiency coefficients for every manufacturer for every year. Efficiency coefficients were the relative scores that took into account the inputs and outputs for all car manufacturers and was derived from a linear-programming technique. In the second stage of the analysis a truncated regression was used to model the efficiency coefficients as the dependent variable and the incidence of internet advertising expenditure as an independent variable. The results suggested that firms which had invested in internet advertising had lower inefficiency scores thereby suggesting that the inclusion of internet advertising as part of the media mix helped to improve their advertising efficiency. However, the study did not provide any specific recommendation to increase the level of IDA. Moreover high correlation between independent variables caused likely endogeneity issues.

Wiesel et al (2011) used a Vector Auto Regression (VAR) model to determine the impact of various media such as paid search advertising, faxes and flyers in driving consumers through a purchase funnel which was sequenced as leads, quotes, orders and profits, and then determine the budget allocation based on the profit contribution of each media. The study's aim was to help a Belgian furniture manufacturer identify the role of each media in the purchase funnel. Whilst the front end of the funnel was manifested in behaviours such as visits to the website, the end of the funnel was indicated by behaviours such as enquiries or purchase orders. Danaher and Dagger (2013) used a method that optimized advertising response for a cross-media campaign to offline sales with budget constraints for each medium. The media that were measured were television, newspapers, magazines, radio, IDA, paid search, social media, email, catalogues and postal mail. Each medium was allocated a budget which was in proportion to its effectiveness. Interestingly the findings suggested that IDA was ineffective in driving offline purchases and thus the recommendation was against any budget allocation to IDA. In another study, Manchanda et al (2006) used a stylised experiment to determine the differences in profit levels by clustering users into four segments, then calculating the probability of a purchase for each segment, and finally arriving at the profitability of each cluster by calculating the difference between the product of the average revenue and an estimated CPM. The method was unique and provided useful pointers for media planning practitioners, though it lacked information to enable calculation of marginal profits per user which would have provided better and more accurate results.

In sum, whilst there have been more studies around determining optimal budget allocation across a broad media-mix which includes traditional and internet media (Naik and Peters, 2009; Pergelova et al, 2010; Wiesel et al, 2011), there have been fewer studies to optimise frequency levels of IDA impressions against a budget constraint (Manchanda et al, 2006). For planning advertising campaigns, guidelines are required by media planning practitioners that provide a ‘bottom-up’ approach to determine an optimal frequency of IDA impressions which are necessary to drive marketing goals. This is a critical area of media planning that needs to be supported through research findings in order to improve the effectiveness of IDA.

Overall, even though there have been a number of researches done in the three sub-fields on the issue of determining optimal frequency levels of IDA impressions, there have been few studies that have comprehensively integrated the three sub-fields together in one single study. The study by Manchanda et al (2006) is probably the exception to the norm and is the most comprehensive one so far. However, this study only evaluated the impact of IDA impressions on repeated purchases and not on first time purchases thereby limiting its applicability. Therefore there is an opportunity to undertake a comprehensive study to determine an optimal frequency level of IDA impressions required to drive online purchases by bridging the learnings from the literature already available on the subject. Moreover, the study was done for a beauty product, a category that has a relatively a lower incidence of online purchase than some other categories such as travel and leisure. Therefore, the findings of the study are less generalizable.

This gap in research to understand the optimal frequency of IDA impressions has also been acknowledged by many researchers. Li and Leckenby (2004) have proposed the development of optimal frequency guidelines in internet advertising as an important area for future research in order to improve our understanding about the effectiveness of internet advertising. Lee and Cho (2010) too have acknowledged the gap in research in this field. Given the growing importance of IDA as reflected in its size and growth, the need to determine optimal levels of IDA impressions to help practitioners in planning their IDA campaigns has become more acute (Bucklin and Sismeiro, 2009).

Perhaps not surprisingly, the lack of sufficient research in this field has been an impediment towards a wider adoption of optimal frequency guidelines amongst practitioners. Less than 50% of media planners use frequency setting for internet advertising as there is a lack of continuity of frequency studies from traditional media (Cheong et al, 2010). As a consequence most media planners continue to plan for IDA impressions in a vacuum, an approach that is clearly inadequate and compounds the negative perceptions that advertisers have about IDA impressions. Cannon (2001) strongly suggested the adoption of media planning concepts that have been developed using advertising in traditional media, to IDA in order to facilitate the wider adoption of an integrated approach to planning and to ensure a fairer comparison and evaluation across media. For the purposes of our study, such relevant concepts would be those on advertising exposure frequency setting, The ensuing literature review section will elaborate on the frequency setting concepts which were developed using advertising in traditional media that still have widespread acceptance amongst practitioners. By relating these concepts to the world of IDA will go a long way in helping practitioners embrace the findings of this study.

LITERATURE REVIEW: UNDERSTANDING THE PREVALENT ADVERTISING EXPOSURE FREQUENCY THEORIES

As the core focus of this study is to develop an optimal frequency level of internet display advertising (IDA) impressions, it is critical to understand the key theories and constructs from studies in traditional media in order to provide the foundation of our understanding of the role frequency plays in driving advertising's effectiveness. This literature review section focuses on the theories that explain the role advertising exposure (impression) frequency has in driving advertising effectiveness, the factors that influence the effect of frequency and the implications thereof in the context of IDA. These findings are largely based on advertising in traditional media such as television, print and radio. As practitioners continue to apply learnings from such theories for advertising on traditional media, it is expected that the adaptation and contextualization of such theories for IDA will improve the chances for findings from this study to gain widespread acceptance within the internet advertising industry.

Advertising exposure frequency theories - Effective frequency and recency

Effective frequency theory: Advertising influences through learning

The first studies on understanding the role of advertising exposure frequency in driving advertising effectiveness emerged around end 1950s, just after the post-World War Two economic boom period (1945-1960). This period witnessed the continuous launch of products and brands that fueled rising consumerism especially in US and Western Europe. Given this scenario, advertising's role was seen as creating awareness about new concepts, categories, products and brands that were being launched in quick succession. Advertisers cared little about regulating and optimizing their advertising weights as they experienced healthy growth in sales year-on-year. However, by late 1950s, as the economic growth started to taper off advertisers turned more cautious in the way their advertising was being deployed. One of the areas which came in for closer scrutiny was the frequency level of advertising exposures. Advertisers started to seek answers to understand the optimal level of advertising exposure frequency that was truly necessary in driving their marketing goals.

Given the background that advertising was seen as a means to informing consumers about new brands and products with the ultimate aim of influencing those consumers to purchase those brands and products, it is not surprising that initial studies tapped into researches in the field of consumer psychology. Naples (1979) mentioned one of these psychology-based researches undertaken by Ebbinghaus in 1885 that demonstrated the relationship between learning, forgetting and repetition required for verbal learning. Ebbinghaus used himself as a subject in an attempt to remember nonsense words by repeating them loudly and then checking on the number of those words he could remember the next day. Through this unique experiment Ebbinghaus noted that the act of repeated learning of meaningless words reduced the rate of forgetting those words. Jakobovits (1966) undertook a study of semantic satiation to explain the phenomenon that repetition of certain words or symbols progressively inhibited cognitive learning. Based on his findings he suggested that the excessive repetition of verbal cues could lead to satiation i.e. inhibition of learning. Whilst he did not indicate the level of repetition at which satiation would be reached, he did suggest that the level of repetition that induces satiation could vary depending on a person's individual characteristics. Such initial psychology based studies aided the initial researches that were undertaken to ascertain lower and upper levels of advertising exposure frequency that would be most effective. The minimum level of frequency of advertising exposures was the level at which learning of the advertised message was triggered and the maximum level of frequency of advertising exposures was the level beyond which learning was inhibited. Building on the learnings gained from the studies in consumer psychology, early researches that analyzed the impact of frequency in advertising exposures supported the idea that every incremental advertising exposure had a differential impact on the desired marketing goal and that the differential impact would vary depending on the time-interval between each exposure. This would in turn impact the relationship between learning and forgetting. Zielske's (1959) study of newspaper advertisement exposures amongst housewives showed that thirteen exposures spread equally over one year compared to thirteen advertising exposures spread equally over just thirteen consecutive weeks generated the highest remembrance of the advertisement at the end of one year. Conversely the intense burst of thirteen consecutive weekly advertisements built remembrance of the advertisements faster, albeit the effect was more temporary. The study provided invaluable insights into the short-term and long-term impact of repeated advertising exposures.

McDonald (1971) probably conducted the first study that directly evaluated the short-term impact of advertising exposures in driving consumer purchases in fifty

FMG product categories. Using daily diary data that was provided by housewives who were asked to record their exposure to media and their product purchase occasions, the study revealed that on an average across the nine product categories whose purchase occasions were being recorded, the advertising exposure frequency required to trigger a brand switch was two. The findings also suggested that an advertising exposure frequency that was below two was insufficient to make consumers switch brands, whilst an advertising exposure frequency higher than two did not provide any incremental benefit. Krugman (1972) proposed the '3-hit' theory which is still widely regarded as the basis for the formalization of the effective frequency theory. He postulated that the first exposure of a brand's advertisement generates 'curiosity', the second exposure generates 'recognition' and the third exposure generates 'decision'. Any subsequent exposures beyond three are simply a repetition of the third exposure and generate no further incremental effects. Krugman (1972) added that as consumers do not forget advertising so easily, a higher frequency beyond three exposures was not necessary. Therefore, he proposed an advertising exposure frequency range of between two exposures as a lower limit and three exposures as the upper limit. Grass et al (1972), emphasized the importance of studying the impact of a frequency distribution of advertising exposures rather than an average frequency of exposures. In this research the authors examined the effectiveness of corporate advertising for the firm Dupont. The findings showed that the attitude scores towards the firm Dupont, increased for every additional exposure of the advertisement and peaked at the third exposure of the advertisement.

Naples's (1979) book, "Effective Frequency: The Relationship Between Frequency and Advertising Effectiveness" which consisted of a compilation of a number of studies done in the 1960s and 1970s, helped to solidify the effective frequency rule of three exposures in the industry. There were a number of pertinent conclusions that Naples made in his book based on his analysis of the studies that he had compiled. Firstly, just one advertising exposure within a purchase cycle was rarely effective in driving effectiveness; instead a minimum of two advertising exposures within a purchase cycle were essential. Secondly, advertising exposures were most effective prior to a purchase occasion within a purchase cycle. Thirdly and probably the most important conclusion was that the most effective frequency level was usually three exposures within a purchase cycle, beyond which the incremental benefits were diminishing in nature.

There was near unanimity on these conclusions made by Naples (1979) in some of the subsequent researches. The work done by other researchers too concluded that a frequency of three advertising exposures was an effective level to maximize advertising effectiveness (Tellis, 1988; Murray and Jenkins, 1992). This effective frequency norm extended to most media such as television, radio and newspapers (Naples, 1979; Chook, 1985; Murray and Jenkins, 1992). Based on a review of 18 studies, Vakratsas and Ambler (1999) too made the generalization that, especially in the case of FMG goods, an advertising exposure frequency of between one and three was sufficient to drive the purchase of a brand.

These findings re-affirmed the thinking at the time that advertising played a powerful role in imparting awareness, learning and knowledge about brands in order to influence consumers' behavior. This was also consistent with the cognition–affect-behavior persuasive model of advertising (Vakratsas and Ambler, 1999), more popularly known as the AIDA model (Awareness–Desire–Interest–Action). This model assumed that advertising worked by first driving cognition (awareness), then affect (desire and interest) and finally behavior (action) amongst consumers through repeated advertising exposures. In sum, effective frequency theory supports the thinking that advertising is a powerful force that influences consumers by imparting learning and knowledge about brands, influencing their (positive) feelings about brands and thereby motivating them to purchase brands.

The summary of the findings of various studies on effective frequency research by Naples (1979) played an important role in the industry-wide adoption of the effective frequency concept. The work by Naples provided the effective frequency theory "a stamp of academic respectability" (Jones, 1997) and became "standard industry doctrine" (Cannon et al 2002). As a result, by the 1980s effective frequency was widely adopted by practitioners working in advertising agencies while making their media planning decisions (Kreshel et al, 1985; Turk, 1988). There was significant increase in the use of effective frequency in the decade between 1982 and 1992 (Leckenby and Kim, 1994) and beyond. The idea that three or more exposures was necessary to drive advertising effectiveness became popular amongst practitioners and is still widely used to this date (Makienko, 2012).

Recency theory: Advertising influences through reminding

Even though the idea that advertising influences consumers via learning became widespread, another alternative idea that challenged this thinking emerged in the 1990s. The genesis of it lay in the continuing decline in the effectiveness of advertising. Two meta-analyses done within ten years of each other, revealed the significant decline in advertising's effectiveness in driving sales. Assmus et al's (1984) meta-analysis of 22 studies showed that advertising's elasticity was 0.22. A subsequent meta-analysis using 389 real world experiments done in 1995 showed that television advertising elasticity was only 0.13 (Lodish et al, 1995). Given that television was usually shown to have higher advertising elasticity when compared to other media (Sethuraman et al, 2011), this decrease in television advertising elasticity and by implication overall advertising elasticity triggered a re-think with the fundamental premise on which effective frequency was based on. This premise, which was the foundation of the effective frequency theory, was whether advertising really worked by educating and motivating consumers or was there another effect at work.

As the number of new categories, products and brands being launched in the developed markets in the western world slowed down in the 1990s, researchers started to question advertising's role of teaching the consumer about new products and brands (Ephron, 1995). Evidence suggested that advertising was not so effective in driving sales of existing brands as compared to newer brands. Lodish et al's (1995) study showed that the advertising elasticity for established brands was considerably lower than that of new brands (0.05 versus 0.26). Thus as more and more brands were now established rather than new, the primary goal of marketers shifted from driving sales in a growing market to defending sales in a stagnant market (Ephron, 2006 pp 9). Therefore advertising's role as a learning medium for consumers, as espoused by the proponents of effective frequency researchers, didn't seem relevant any more.

Instead a group of researchers suggested that advertising's role was more modest (Jones, 1995a; Ephron, 1995). Rather than imparting consumers with knowledge about new products and brands, advertising was seen to play the role of a reminder that nudged consumers to simply choose one brand over another. Barnard and Ehrenberg (1997) and subsequently Ehrenberg (2000) theorized that advertising's role was primarily defensive, i.e. to protect an existing brand's market share by reinforcing the buying behavior of a brand's current users and was relatively ineffective in converting new consumers. This new thinking emerged from the findings of single-source data that measured the Short Term Advertising Strength (STAS). This research was undertaken by Jones (1995a) whose findings were published in his book "When Advertising Works: New Proof That Advertising Triggers Sales." The theory was based on findings from a unique single-source panel which captured for the very first time advertising exposures and purchases made by consumers in a single data source. Jones' (1995a) research showed that the highest number of incremental consumer purchase occasions occurred after just one advertising exposure, and the number of incremental purchase occasions that occurred after more than one advertising exposure, increased, but at a diminishing rate. To add to this finding was the fact that most of those purchases were repeat purchases for the same brand. This suggested that the primary role of advertising was to serve as a reminder for the consumer to 're-choose' the brand which had been purchased earlier and that one exposure alone delivered the highest number of incremental purchases.

Another key finding was that advertising exposures that occurred in the week of the purchase had a higher impact than advertising exposures which had occurred in the weeks preceding the purchase. This also led to the conclusion that a single exposure was sufficient to drive a purchase and that the closer the exposure was to the purchase occasion, the more effective would that exposure be. This meant that a consumer would be most receptive to an advertising message just before he or she made a purchase (Ephron, 2006 pp 7). Therefore in order for an advertising exposure to be effective it ought to be as close or 'recent' as possible to a purchase occasion (Ephron, 1995; 1997; 2005; 2006). This new approach to advertising planning was therefore termed as <u>recency planning</u> (Ephron 1995).

Though recency theory postulates that advertising primarily drives short-term sales as advertising relies on the effect of one advertising exposure on an immediate potential sale, Jones (1995a pp 60; 1995b; 1997) stated based on his research findings that consistent increases in short-term sales also leads to increases in long-term sales. This results in part due to the cumulative impact of multiple short-term sales increases as well as brand momentum gained due to repeated purchases (Newstead et al, 2009). However, the long-term sales effects are generally lower than the short-term effects which is usually the case as advertising is generally not present continuously. Longman (1997) too echoed the above findings after his review of a research by Donius and Gonten (1997) that showed the incremental effect of short-term purchases in driving long-term incremental repeat purchases. In fact based on his evaluation of 63 TV ad copy tests, Longman (1997) concluded that short-term effects were critical in driving long-term success of advertising. Newstead et al (2009) too made a similar conclusion after their review of many studies based on single-source data. Whilst the sales impact of a more recent advertising exposure is the highest thus indicative of a short term effect, every exposure's effects cumulatively add up and ultimately have a long-term sales effect (Reichel and Wood, 1997). In effect, based on the recency theory, an advertising exposure has mainly a strong short-term effect, and a smaller and indirect long-term effect on sales.

In sum, recency theorists alluded to the fact that advertising is a relatively weak force, and only has the ability to nudge a consumer to re-purchase a brand. It acts as a reminder, works largely through a short-term effect and has no lasting impact on influencing consumers. Any long-term impact is largely due to a cumulative effect of short-term effects driven by repeat purchases. This is in direct contrast to the effective frequency camp which theorizes that advertising has a powerful influencing role on consumers in driving knowledge and learnings about a brand which in turn encourages them to purchase the brand.

From a frequency setting standpoint, findings from both of the above theories had significant impact on the practice of advertising media planning. Whilst effective frequency theory proposed that repeated or multiple advertising exposures (usually three) were necessary, recency theory proposed that just one exposure was enough. Even to this date most practitioners apply either of the two theories whilst determining an appropriate level of advertising exposure frequency especially when planning for advertising on traditional media.

Advertising exposure frequency and spacing (or time-period)

Both effective frequency and recency theorists have alluded to the importance of measuring the impact of advertising exposures within a specified time interval or ‘spacing’. This is fundamental to the application of the two advertising exposure frequency theories (Sawyer et al, 2009). Spacing consists of two parts. The first is the spacing between advertising exposures, i.e. the intra-exposure time between two advertising exposures. The second is the spacing across advertising exposures, i.e. the cumulative time between the first and the last exposures that occur across repeated advertising exposures.

The primary reason for accounting for the spacing effect for a study of advertising exposure frequency effectiveness is the fact that the effect of an advertising exposure decays over time. Proponents of effective frequency emphasized the need to measure the effects of frequency within a reference of time (Ostheimer, 1970). As the effects of advertising exposures start to decay almost immediately after they appear, the effect of a similar number of exposures but across different time frames would be very different. He highlighted this point by quoting the study by Zielske (1959) that showed the hugely different impact of two schedules with the same number of advertising exposures but with different time-periods. In the study a 13 week advertising schedule with one exposure per week built advertising recall faster than a 52 week advertising schedule with one exposure for every 4 weeks. On the other hand, the 52 week advertising schedule managed a higher recall at the end of the year than the 13 week schedule. In a similar study done on television, Zielske et al (1980) studied five different television schedules and showed that television schedules that were more evenly spread out across one year, had not only slower learning rates but also slower forgetting rates than those schedules where the television spots were concentrated within fewer weeks. This was re-affirmed from the findings of experiments that measured the effectiveness of advertising exposure frequency across different time intervals. One such study was undertaken by Heflin and Haygood (1985), who suggested that the most effective television advertising scheduling was the one in which the spots were neither too concentrated within a day, nor were they too spread out across many days. The study concluded that the most effective television schedule was the one in which the spots were spread across an interval of between one to three weeks. Clearly these studies suggest that an understanding of the most appropriate time interval within which advertising exposures need to occur is critical to our understanding of the effectiveness of repeated advertising exposures. McDonald (1995 pp 23) made the point that frequency has no validity unless its effects were measured for a defined period. Therefore in order to make a fair comparison of the effectiveness of different advertising exposure frequencies it is critical that the time-interval within which the advertising exposures occur is held constant.

Whilst for recency, owing to its adherence to the idea of a single exposure, the point about time between or across exposures does not arise, the concept of spacing is still inherently relevant for its successful implementation. Recency postulates that a single advertising exposure closest to a consumer's moment of purchase is most effective in driving sales. Therefore an exposure to a single frequency will impact only those consumers who are closest to the moment of purchase. The effectiveness of applying a recency strategy is hugely dependent on identifying as large a number of consumers who are likely to purchase, and then targeting them with a single exposure. However, this is problematic to implement as at any given time only a small number of consumers are actually looking to purchase and they are not easily identifiable. Faced with this potentially intractable issue, recency theorists framed the impact of a single exposure within a time frame of a purchase cycle which is usually of a one week duration for a FMG category. Therefore the advertising exposure strategy as espoused by recency is to maximize unique reach in a flight of one week (Naples, 1997). An inevitable outcome of this strategy is that a number of consumers will potentially be exposed to an advertising exposure frequency of greater than one before they actually make a purchase. This is due to the fact that in reality only a very small number of consumers actually make a purchase of the same product every week. As a result, Ephron (1995) recommended a continuity strategy that ensured a maximum number of single advertising exposures to unique consumer per week for every week in a year. His recommendation was based on the premise that a frequency of more than one per week would not significantly add to any incremental gain whereas spreading a frequency of one beyond one per week would dilute the effectiveness of the advertising exposure. This is because a longer time interval between exposures could lead to 'forgetting'. Thus such an approach of a series of single exposures over a shorter temporal framework inevitably leads to a strategy of multiple frequency of exposures over a longer temporal framework with an even spacing of one week between exposures. This was well articulated by McDonald (1997) in his quote that "a frequency of 1 exposure in a week (as proposed by recency theory) means 4 exposures in a month". The recommendation by recency theorists to have moderate advertising weights per week (Ephron, 1995; Reichel and Wood, 1997) has the effect of spreading the possible effects of multiple exposures across a period of between one to four weeks. This turns out to be a similar recommendation as the one made by effective frequency theorists.

Whilst both the theories provide similar recommendations for media practitioners in that these theories ultimately recommend multiple or repeated advertising exposures, the crucial difference lies in the quantum of spacing of advertising exposures. Effective frequency recommends multiple frequency over shorter periods of time (such as a gap of one to three days between exposures spread over a period of one week), whilst recency recommends a gap of one week between exposures irrespective of the campaign period. Thus any study to determine the optimal frequency level of IDA impressions should take into consideration the spacing or the time-interval between and across repeated advertising exposures.

Effective frequency & recency theories and advertising response curves

The fundamental premise of the effective frequency model is that it is based on the assumption that the advertising response curve is 'S-shaped' (McDonald 1971; Jones, 1997). Statistical models developed by researchers to best represent and predict the relationship between sales and advertising indeed showed the existence of the ‘S-shaped’ response function. Rao and Miller (1975) whilst proposing a new non-linear distributed lagged model to link market share with advertising and promotional spends for five FMG brands in the US, showed that the advertising response function followed an ‘S-shaped’ curve. Likewise a model derived and tested on eight FMG product categories in Australia too showed an ‘S-shaped’ response curve between sales and advertising (Metwally, 1980). The ‘S-shaped’ response curve is caused due to the effects of the wear-in and wear-out phenomenon. Wear-in is the phenomenon of increasing effectiveness of advertising due to advertising exposure repetition (Pechman and Stewart, 1988, Tellis, 2009). This is based on the premise that advertising works by making consumers learn about a product or a brand (Krugman, 1972; 1975). Based on the psychology of a learning situation, a stimulus needs to be grasped first, then seen as relevant and only then applied. In such a case, the initial consumer response to an advertising exposure is low (when the consumer is still grasping the message) and then it picks-up steeply at an increasing rate after the second exposure (when it becomes relevant to the consumer). Wear-out is the phenomenon of decreasing or lower effectiveness of advertising due to advertising exposure repetition (Pechman and Stewart, 1988, Tellis, 2009). In the same learning situation described above, the rate of increase of the consumer response will decline after the third exposure and beyond (once learning is complete and no additional learning takes place) (McDonald, 1997).This can occur due to reasons such as advertising exposure repetition signaling doubts about the quality of the brand (Kirmani, 1997), boredom or satiation (Chatterjee et al, 2003). Therefore the ‘S-shaped’ response curve is the result of higher wear-in than wear-out occurring during the first few advertising exposures which then reverses to higher wear-out than wear-in occurring during the subsequent advertising exposures (Tellis, 2009). Therefore, the presence of an ‘S-shaped’ advertising response curve implies that repeated advertising exposures are desirable in order to drive advertising’s effectiveness. This further suggests that there could be an optimal level of such repeated advertising exposures that maximizes the level of advertising responses.

The recency model is based on the premise that most advertising response curves are downward concave shaped, i.e. exhibit diminishing returns, with the first exposure having the maximum effect, the second exposure lesser than the first, and so on (Jones, 1995a; 1995b; 1997; Longman,1997; Schroeder, 1997, Roberts, 1999). This challenges the principle of effective frequency by questioning the assumption behind the ‘S-shaped’ advertising response curve (Ephron1995, 1997; Jones, 1995a; 1995b; 1997) that the assimilation of advertising messages require multiple stages. Research studies showed the widespread prevalence of the diminishing advertising response curve rather than an ‘S-shaped’ response curve (Simon and Arndt, 1980; Cannon and Riordan, 1994). Research using single-source data for 78 American FMG brands revealed that advertising had diminishing returns to sales, i.e. the advertising response function was downward concave shaped (Jones, 1995a; 1995b). Jones (1998 pp203-214) interpreted prior findings of a single-source research done by the Starch organization in New York during the period 1944-1960 as a strong validation of the existence of a diminishing advertising response curve for magazine advertising. Other researchers using similar single-source data re-affirmed that most advertising response curves were indeed not ‘S-shaped’, but were instead downward concave shaped (Taylor et al, 2009; 2013). McDonald (1997) whose research was one of the basis for Naples's work on effective frequency, himself admitted that the advertising response curves in his research for advertising were generally not 'S-shaped, but were instead mostly downward concave shaped.

The implication of findings from studies that espoused recency on advertising exposure frequency setting was significant. The researchers did not imply that a higher frequency didn't work, instead they simply implied that for every unit of investment, the advertising response from a single advertising exposure will be considerably higher than multiple advertising exposures due to the diminishing advertising response curve. In effect, a frequency of greater than one was a lot less cost-effective than a frequency of one (Ephron, 1995; 1997; 2006 pp 71). Therefore it was more effective to expose advertising once to as many potential consumers, than to expose advertising multiple times to a few potential consumers (Ephron, 1997; Longman, 1997). In other words, for the same amount of budget, a single advertising exposure rather than repeated advertising exposures, would drive higher advertising responses at an aggregate level.

MODERATING IMPACT OF CONSUMER CONTEXT

Based on the literature review, the findings and the arguments put forth by the two camps of advertising exposure frequency setting, i.e. effective frequency and recency, there seem to be two mechanisms through which advertising works with fundamental implications on determining optimal advertising exposure frequency levels. The first, as espoused by the effective frequency theorists, is that advertising works by imparting knowledge and learning to consumers about brands and products thereby triggering a need to purchase. In other words, as this alludes to the existence of S shaped ad-response curve, multiple frequency of advertising exposures (rather than just one) will be necessary drive response to advertising. The second, as backed by the recency theorists, is that advertising works primarily by reminding consumers about brands at an opportune moment just prior to a purchase. This alludes to the existence of the downward shaped concave advertising response curve, which in turn implies that just one advertising exposure should suffice to drive a response.

The fact that neither of the two theories can be applied universally at all times and in all situations, was indirectly alluded to when researchers laid out exceptions to their respective theories' applicability. In fact upon being challenged about the universal applicability of their respective concepts, researchers from the respective camps clarified that a blanket application of effective frequency or recency was neither recommended nor was feasible (Naples, 1979; Jones, 1995a pp 186; McDonald, 1995 pp 117-127; 1997; Naples, 1997). These researchers clarified that an application of a single frequency, i.e. recency, or multiple frequency, i.e. effective frequency, across brands and products at all times is not appropriate as the context under which each of the two theories are applicable can vary at different times for each individual consumer. In order to reconcile the differences between the learning camp as represented by the effective frequency theorists and the reminding camp as represented by the recency theorists, other researchers laid down the broad contexts under which either of the two theories would be more suitable and appropriate (Ramond, 1974 pp 55; Tellis, 1988;1997; 2009; Makienko, 2012). They agreed that the application of the idea that 'one exposure is enough' or 'three or more exposures are necessary' is contextual to the consumer. It is directly related to whether the consumer is in a learning or a reminding situation, and that is in turn linked to a consumer's involvement with the product and a consumer's level of familiarity with the brand. We will now examine the influence that these two contexts have on the shape of the advertising response curve to advertising exposure frequency.

Impact of consumer involvement on ad-response to advertising exposure frequency

Though consumer involvement has been defined in many different ways, there is a broad consensus that it is a function of a consumer's ability and interest in a product. Greenwald and Leavitt (1984) defined it is as the level of 'attentional capacity' of resources required to attend to a message source by a consumer. Buchholz and Smith (1991), based on their literature review on consumer involvement, summarized it as "the extent to which a stimulus or task is relevant to consumers' existing needs and values." Rossiter et al (1991) clarified that consumer involvement will vary at an individual level depending on a consumer's personal interest in the product. Researchers have classified a consumer's involvement with a product in many ways. Greenwald and Leavitt (1984) defined consumer involvement as comprising of four stages – pre-attention, focal attention, comprehension and elaboration. Hsu and Hsu (2011) listed three main aspects to involvement – motivation, ability and opportunity. Vaughn (1980; 1986) suggested that consumer involvement for a product is a continuum between two extremes – high involvement and low involvement. In order to simplify the operationalization of high and low consumer involvement amongst practitioners Rossiter et al (1991) made a broad generalization in which he categorized entire product categories as being amenable to high or low consumer involvement. Products of higher value (price), with occasional purchases and entailing higher risk were classified as eliciting high involvement from consumers (e.g., financial products) and products of lower value, being habitual in nature and entailing lower risk were seen to be eliciting low involvement from consumers (e.g., FMG products). The above classification, though an oversimplification, alludes to the possibility that a consumer's level of involvement could even vary within a product category.

A consumer's learning and reminding situations can naturally occur in cases of both high and low involvement products. Much of the research on both effective frequency and recency has been done on FMG products which are low involvement in nature. In learning situations for low involvement FMG products such as those alluded to by Krugman (1965; 1972; 1975) the challenge for advertisers is to influence consumers into switching to lower priced, frequently purchased and harder to convince products. In learning situations for such low involvement products a frequency of three or four exposures within a week (as it is the duration of a purchase cycle) is necessary (Naples, 1979). On the other hand in reminding situations when most consumers are already aware and familiar with the brands in the category, a single exposure within a purchase cycle will suffice (Ephron, 1995). This was the situation which was most cited by recency theorists as most of their research was done in the low involvement FMG category in markets that were stable, and consumer knowledge about the brands in the category was high (Taylor et al, 2009). Therefore in case of low involvement products, a high frequency of three or four exposures within a week is desirable in a learning situation, whereas a single frequency will suffice in a reminding situation.

In the case of high involvement products, consumers will tend to make a more considered purchase as their involvement is higher due to higher risk of a loss should the product not match expectations (Vaughn 1980; 1986). In such categories, the awareness of products tends to be lower and uncertainty amongst consumers about performance is higher (Vakratsas et al, 2004). Therefore for high involvement products the task of imparting learning, i.e. knowledge about a product and its benefits, will be more long drawn out as the amount and complexity of information required in order for a consumer to make a decision is of a higher degree than it is for low involvement products. Given the complexity and quantity of information it is quite likely that not all this information is fully understood in the first exposure. As a result wear-in may be delayed and more exposures may be necessary for the message to be fully understood. Also, due to the complexity of the message and the higher interest in the product category, satiation or boredom with the message may also be delayed as the consumer will tend to find something new and interesting in every incremental advertising exposure. As a result the advertising response curve for high involvement products may not diminish after the first exposure.

Two studies that evaluated long-term effects of advertising, i.e. impact of advertising in learning situations for high involvement products, showed that the advertising response curve was ‘S-shaped’ and was across a longer time frame. A study sought to examine whether a threshold level exists beyond which advertising starts being effective, in other words whether an ‘S-shaped’ advertising response curve does exist (Vakratsas et al, 2004). The study indeed found evidence that such a threshold does exist for high involvement categories such as SUVs and that the advertising response was across a longer time which was. five years. Another study that showed evidence of the long-term effectiveness of multiple exposures for a high involvement product, which in this study was Dupont’s corporate brand image, did so across a period of eight months (Grass et al, 1972). In case of a reminder situation where a consumer is already knowledgeable about a brand, the wear-out of advertising exposures for a high involvement product will expectedly be faster than in a learning situation. A short-term analysis of advertising for high involvement categories such as financial products and automobiles showed very high wear-out when the exposures occurred within a day (Havlena and Graham, 2004).

Vakratsas et al (2004) concluded that advertising response curves for categories where consumers have a higher involvement such as cars and SUVs were likely be ‘S-shaped’. On the other hand the advertising response curves for categories where consumers have a lower involvement such as liquid detergents were likely to be downward concave shaped. This suggests that in case of high involvement products a higher level of advertising exposure frequency may be more effective than a lower advertising exposure frequency. Tellis (2009) concluded that advertising wear-out was slower in case of infrequently purchased goods and tended to be faster for FMG goods.

Tellis (2009) after reviewing studies on advertising, re-iterated the importance of consumer context in determining the impact of advertising frequency levels. A more involved consumer is likely to be impacted with a lower frequency of advertising exposures versus a lower involved consumer who is more likely to be impacted by a higher frequency. Two researches undertaken by Jeong et al (2011; 2012) to understand the effectiveness of repeated TV advertising on Super Bowl in driving brand recall, advertising recall and brand recognition showed that in high involvement categories such as automobile and services the impact of product category was lower than average which suggested that a higher frequency of exposures rather than a lower frequency of exposures had a greater impact in driving effectiveness. The effect was the opposite for low involvement categories such as household products.

In summary, research suggests that level of advertising exposure frequency will vary across product categories depending on whether the consumer involvement with the product categories is high or low, and will further vary depending on the presence of a learning situation or a reminding situation. We can further conclude that the level of advertising exposure frequency will be higher when a consumer has higher involvement compared to when a consumer has lower involvement regardless of the product category.

Impact of brand familiarity on ad-response curve to advertising exposure frequency

Consumer's familiarity with a brand is the sum total of all brand associations that are present in a consumer's memory. More are the associations a consumer has about a brand, more is the consumer's familiarity with that brand. Conversely lower are the associations a consumer has about a brand, lower is the consumer's familiarity with that brand (Campbell and Keller, 2003). The associations that a consumer has about a brand are a result of all the experiences, whether direct or indirect, that a consumer has with a brand (Kent and Allen, 1994). A consumer's experience with a brand could either be as a result of the consumer's prior purchase and/or usage of the brand, or as a result of a consumer's exposure to the brand's communication. A consumer's experience could also be as a result of an experience shared by someone else who then relates it back to the consumer (Campbell and Keller, 2003). Tellis (1997) emphasized that consumer's brand familiarity will vary at an individual level. He explained brand familiarity as a function of three attributes – consumers' knowledge about a brand, consumers' experience with a brand and consumers' loyalty with a brand.

Tellis (1997) provided the reasons as to why advertising of familiar brands will be more impactful compared to advertising of less familiar brands. Advertising of familiar brands will garner higher attention as consumers will selectively pay more attention to familiar brands' advertising especially in a scenario of high competitive clutter. Moreover such advertising will relate better with consumers as consumers will identify with it better owing to their existing brand association. Finally, advertising of familiar brands will be interpreted more favorably by consumers as they will seek to justify their current associations with the brand. In such a situation, the role of advertising is simply to remind the consumer about the brand so as to consciously revive the dormant brand associations already present in the person's memory. On the other hand advertising of brands with lower familiarity have fewer opportunities to be noticed, to be related to and be identified with. Therefore advertising's task is to enable the building and learning of associations with the brand for which a greater advertising intensity is needed. This suggests that brands with high familiarity will have a diminishing advertising response curve, whereas brands with low or no familiarity will have an 'S-shaped' advertising response curve.

Whilst there is a plethora of evidence to show the presence of the diminishing/downward concave advertising response curve in the case of a reminding situation (i.e. high brand familiarity) in low involvement FMG products, there is also evidence to validate the presence of a ‘S-shaped’ advertising response curve that is characteristic of a learning situation (i.e. low brand familiarity) in low involvement products (Tellis 1988; Tellis, 1997). Vakratsas et al’s (2004) findings showed that the likelihood of an ‘S-shaped’ advertising response curve occurring when a brand was new (and therefore less familiar) was higher than when a brand was older (and therefore more familiar).Taylor et al (2009) showed in an analysis of 28-day advertising response curves for five butter and butter substitute brands that brands with lower market shares did not exhibit a diminishing advertising response curve so characteristic of large established brands; rather they had a flat/constant advertising response curve.

Naples (1979, pp 55; McDonald, 1995 pp 121-122) concluded that for large brands an exposure of one may suffice unlike for smaller brands where a higher frequency will be necessary. Machleit and Wilson (1988) in an experiment demonstrated that repeated advertising exposures drove brand attitudes via direct effects from emotional feelings and attitude toward advertisements especially for unfamiliar brands. Tellis’s (1988) study showed that familiar brands needed an exposure frequency of between two and three in order to drive a brand purchase, whereas unfamiliar brands needed an exposure frequency of up to seven exposures to achieve the same task. Moreover, he hypothesized that perhaps an even higher exposure level may be effective for very unfamiliar brands, which the study was unable to verify as it had limited the manipulation of exposure frequency to seven. Kent and Allen (1994) showed that consumers with higher brand familiarity recalled advertisements better than those with lower brand familiarity after controlling for frequency and timing of advertising exposures. Dahlen (2001) too showed that a high exposure frequency of around five exposures drove brand attitudes for unfamiliar brands whilst conversely (Ephron 1995) suggested that in cases of highly familiar brands a single exposure was most effective. Ramond (1974 pp 55), in his analysis of various studies on the effectiveness of frequency of exposures stated that one exposure was enough when someone was already pre-disposed to buy, two exposures were necessary to cause a brand switch and three exposures were required to learn and buy an unfamiliar brand. In other words, a single exposure was enough as a reminder to ensure a repeat purchase of a familiar brand, whilst two or more exposures were necessary for a consumer to learn about a brand bought less often or for a completely new brand. Similarly, Makienko (2012) suggested that a frequency of greater than one was necessary to drive advertising effectiveness for new or less familiar brands and products.

To summarize, the level of brand familiarity determines whether the consumer is in a learning situation or a reminding situation. In case of high brand familiarity, the consumer simply needs to be reminded and therefore fewer exposures are required to drive advertising's effectiveness. On the other hand in case of low brand familiarity, learning about the brand needs to be imparted and therefore a higher frequency of advertising frequency is necessary. Tellis (1997) sums up the findings of research on advertising frequency by concluding that optimal frequency levels were moderated by consumers' familiarity with brands in that all other things being the same, familiar brands needed lower frequency of exposures than unfamiliar brands.

OTHER FACTORS THAT INFLUENCE ADVERTISING RESPONSE

Beyond the frequency of advertising exposures, there are a number of other factors that have an impact on the responses to advertising. These factors can broadly be classified as campaign related, media related, and seasonality related. Even though both effective frequency and recency theorists have alluded to the important of factoring these variables in to determine optimal advertising exposure frequency levels (Naples, 1979, Ostrow, 1984; Tellis 1997; Tellis 2009; McDonald 1995; Rossiter and Danaher, 1998; Sissors and Baron, 2002 pp 110-111; Makienko, 2012), very few frequency related researches have actually demonstrated their impact. Most of the studies have been confined to specifically testing the impact of such factors in stand-alone studies. The key findings based on such researches are summarised below.

Impact of campaign on advertising response

Researches have highlighted the impact differences in the various individual elements of a campaign make on advertising response. These individual campaign level differences include the campaign type – direct response or brand, and campaign advertising creatives – size, shape, use of colour and the use animation (only in case of IDA).

A study by Broussard (2000) showed that a lower frequency was required for IDA advertisements with a direct response message, whilst a higher frequency was required for IDA advertisements with a brand message. A lab study undertaken by Bellman et al (2010) showed that the first advertising exposure of a direct response interactive television advertisement drove 98% of the direct responses and a mere 2% responses were triggered by subsequent advertising exposures. These findings suggest lower advertising exposure frequencies are required by direct response campaigns when compared to brand campaigns.

Amongst studies which have evaluated the impact advertising creative format, a study that analysed the impact of advertising frequency on attitude towards the advertisement showed that an increase in repetition of up to five exposures for both colour and black & white advertisements improved perceived quality of the product as well as the credibility of the manufacturer (Kirmani, 1997). However, a further increase of seven exposures caused a drop in the perception of product quality and manufacturer credibility in case of colour advertisements but not in case of black and white advertisements. The author surmises that this drop could be the result of the high repetition of colour advertising exposures signalling the effects of poor quality. Other studies have highlighted the differences in impact due to differences in size or length of the advertising message. Danaher and Mullarkey (2003) suggested that a longer or larger advertisement had a higher probability of being noticed as a longer or larger format allows for higher absorption of the advertising message content and therefore being more effective. As a larger advertising format size enables audiences to understand the messages much faster, larger advertising formats tend to wear-in faster than smaller advertising formats. (Jeong et al, 2011) in their analysis of television advertising on Super Bowl suggested that larger advertising formats required lower levels of exposure frequency whereas smaller advertising formats required higher levels of exposure frequency, in order to be effective. Other researchers such as Ostrow (1984) and Rossiter and Danaher (1998 pp 36-37) have provided guidelines that recommend the adjustment of exposure frequency levels for advertising in traditional media upwards in case of smaller advertisement sizes and lower in case of larger advertisement sizes.

In the case of IDA, widespread use of animation and flash technologies has made most advertising creative messages combine elements of direct response and branding. Studies that analysed the use of animation in IDA have found no significant differences between formats with and without animation (Chandon et al, 2003; Zorn et al, 2012). In terms of impact of sizes, whilst some research findings have suggested higher response rates for larger advertisement creative sizes (Baltas, 2003), other researches have not found any significant differences in response rates across sizes and formats citing insignificant or minute differences in the various formats that were tested (Dreze and Hussherr, 2003). As the common practice is to use a mix of sizes and formats in every campaign, with the more popular sizes such as the 729 x 90 being accorded the largest share, the benefit in understanding the optimal level of advertising exposure for IDA impressions at a creative level is rather limited. Instead, evaluating differences by campaigns will be a lot more relevant as well as practical whilst measuring the impact of advertising exposure frequency on advertising response. A similar approach was adopted by Jones (1995a) in his singular work that formed the foundation of the recency theory wherein he analysed four categories of campaigns classified as Alpha One, Alpha Two, Beta and Gamma. The basic principle behind this classification was the success rate of the campaigns in terms of driving purchase occasions amongst consumers. Lee and Briley (2005) too analysed the effect of IDA impression frequency on message recall at a campaign level.

Impact of congruency or 'premiumness' of media vehicle on advertising response

A media vehicle's congruency is the degree to which a media vehicle's editorial content and style is aligned to the nature and messaging of the advertised product. Broadly, practitioners believe that an advertised product's advertising will be more effective in a congruent environment. This is the reason that advertising for cars usually appears in automobile magazines, and advertising for cosmetics dominates beauty and lifestyle magazines. A similar trend is noticed in other media vehicles as well. Studies have shown that the congruency of the media vehicle can influence the impact of an advertisement placed in that media vehicle due to convergence of the media vehicle's perception with that of the brand (Dahlen, 2005). Congruency effects can also occur due to priming effects of the media vehicle's content that influences the way a consumer interprets the advertised brand (Yi, 1990).

Studies have shown that the advantages of advertising in media vehicles that are congruent with the advertised product. A study showed that credibility of the advertising, attitude toward the advertising and brand attitude increased when the advertised brand was in a congruent media versus a non-congruent media (Dahlen, 2005). The study was done using print advertisements that depicted brands placed in unusual but congruent contexts. Another study indicated that an advertisement for a product drove higher brand attitudes when the advertisement was placed in a website that was congruent with the product than when the advertisement was placed in a website that was incongruent with the product (Flores et al, 2014). In the study, the congruency condition was simulated when an advertisement for a video-playing smartphone was placed in a video website and an advertisement for a news-magazine was placed in a newspaper website. In the same study the incongruency condition was simulated by placing the two advertised products in the reverse combination of websites. A research by Cho (1999) showed that when the content in the website had more relevance to the product advertised, there was a higher probability of the advertising to be effective. Yaveroglu and Donthu (2008) showed that in a content-relevant website a single advertising creative was effective in driving brand name recall. In comparison, in a content non-relevant website more varied advertising exposures were required. Importantly they showed that brand recall and intention to click was higher in a website with relevant content than in a website with non-relevant content. Cho's (2003) experiment showed that audiences tended to click more on IDA banner advertisements when the products advertised in the banner advertisements were congruent with the content of the website in which they appeared. He alluded this to two benefits of media congruency - one that the media congruency ensures that the advertising message is closer to what the audience is interested in, and second that media congruency ensures a smoother and less disruptive engagement.

Media vehicle’s influence is also dependent on the status and ranking of a media vehicle. Certain media vehicles due to the fact that they are well established and are seen as being credible have more influence on users. Such media vehicles generally tend to be the more dominant or established ones and also have content which is seen as being reliable and trustworthy. This evokes a higher level of confidence in the media vehicle amongst users. An advertising message that is placed on such credible media is likely to face lower resistance from users as they will subject it to fewer counter arguments and accept the advertising message more readily (Shamdasani et al, 2001). Rossiter and Danaher (1998 pp 30-31) listed the media vehicles that have high source credibility such as primetime television, the most read newspaper and magazine titles, radio news headlines and large static outdoor sites. Such media vehicles will be more effective than others in driving advertising responses as they command higher levels of attention and credibility. As a result advertising on such media vehicles is also likely to be more impactful.

In the case of IDA, websites with higher congruency and/or stature are usually classified as being premium in nature. In case of a travel related advertiser, an example of a website with higher congruency will be TripAdvisor.com as it is a travel related site. An example of a high stature site would be Yahoo.com.sg as it is one of the most visited websites. Advertising exposures (impressions) inventory on such websites is generally bought directly from the publisher. In contrast to premium media, there is mass media which consists of impressions usually bought across thousands of smaller websites which are neither congruent nor of a high stature. Mass media inventory is usually purchased through an advertising network that acts as an intermediary to the smaller websites.

Impact of season on advertising response

Few studies have evaluated the impact of season on advertising response. A few studies have evaluated differences in advertising response curves across day-parts such as the one by Naples (1979) wherein he evaluated differences in advertising response curves to varying levels of advertising exposure frequency in television advertising. In case of internet, there have been limited studies that have studied the impact of day-parts or day of the week on advertising effectiveness. A study that analysed internet users' behaviour in the US alluded to the fact that just like television users, internet users too exhibit varying behaviours across different times of the day (Beyers, 2004). For instance, some of the findings suggested that during the afternoon internet users tend to undertake exploratory and leisure activities such as playing online games and downloading entertainment content. On the other hand, during the evening and night internet users indulge in goal oriented activities such as looking for information on products and making online purchases. However, there seems to be little research that has factored in seasonality while determining the effectiveness of advertising exposures.

PROBLEM STATEMENT

The focus of the study is to determine the optimal frequency level of IDA impressions that drives highest online purchase rate and/or the highest profit. In order to achieve this objective the research problem can be detailed out as follows:

1. Determine the relationship between the dependent variable i.e. online purchase conversion rate and the independent variable, i.e. frequency of IDA impressions.
2. Understand the moderating effects of high/low consumer involvement and high/low brand familiarity.
3. Examine the interaction effects between high/low consumer involvement and high/low brand familiarity with spacing of IDA impressions.
4. Control for the impact of factors such as quality of inventory (premium/mass), and season (festive/non-festive).
5. Determine the optimal frequency for IDA impressions that drives the most sales revenue.
6. Measure the ROI for each frequency distribution level, by comparing the cost of IDA impressions against the conversion revenue generated.
7. Undertake the above using big data, extracted from ad-server log files for real campaigns for a brand in the travel and leisure category based in South East Asia and then accounting for internet advertising issues such as viewability and cookie deletion.

HYPOTHESIS SETTING

The IDA ad-server log data is for an integrated resort brand located in Singapore. The product offerings consist of attractions, entertainment shows, food and beverage outlets, a casino and hotels. Amongst these product offerings, those which are regularly advertised through IDA and can be purchased online are tickets to attractions and entertainment shows. The advertisers deploys a number of IDA campaigns during the year targeting potential consumers residing in the home market, Singapore, as well as in the overseas markets in rest of South East Asia including in countries such as Malaysia, Philippines and Hong Kong.

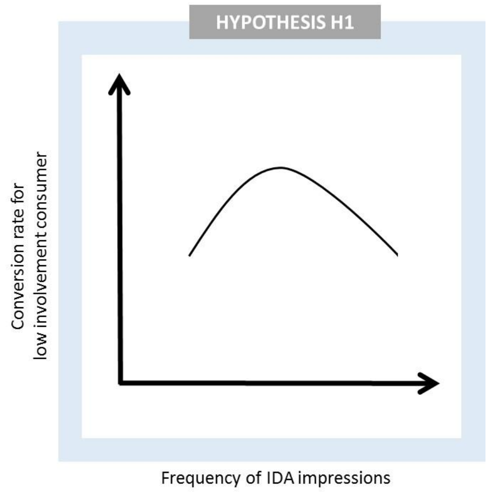
IDA impression frequency and consumer involvement

Researchers have alluded to the fact that advertising media have inherent characteristics that tend to evoke high or low involvement from consumers. Television, which has been the subject of most of the studies that analyzed the impact of frequency of advertising exposures, is seen as a powerful medium that can ‘move’ less involved or passive consumers (Krugman, 1965). This is due to television’s ability to dispense emotional messages to audiences via the combination of moving images and sound (Sissors and Baron, 2002 pp 232-233). This in turn evokes powerful emotions amongst even less involved consumers which suppress rational counter-arguments and thereby improve the effectiveness of advertising messages (Heath, 2011). Couple this with the fact that television ensures forced exposures (Dijkstra et al, 2005) and wider reach (Taylor et al, 2013; Romaniuk, 2013) gives the medium a powerful ability to influence relatively low involved audiences even with a single exposure (Buccholz and Smith, 1991). Non-television media such as print and radio are seen to elicit higher involvement from consumers as it forces consumers to deepen the activation of their senses, as only a fewer senses are activated at a time by these media (Buccholz and Smith, 1991) as compared to television.

Internet is unique as a medium, as it elicits both high as well as low involvement from consumers. Consumers can be in a goal-directed mode by actively searching for information on search engines and then clicking on paid search advertisements, thereby demonstrating a high level of involvement (Danaher and Mullarkey, 2003). On the other hand consumers may merely be surfing the internet without any specific goal and simply undertaking 'exploratory' behavior that is less involved (Danaher and Mullarkey, 2003). Therefore, by understanding consumers' behavior on the internet, it is possible to classify consumers as being high or low involvement. Those who search and click on search advertisements can be classified as high involvement consumers, and those who only surf and are therefore exposed only to IDA impressions can be classified as low involvement consumers. This type of classification is backed by researchers who have highlighted the differences between IDA and paid search advertisements by terming them as unsolicited and solicited advertisements (Ha, 2008), incidental and deliberate advertisements (Ha, 2008), intrusive and non-intrusive advertisements (Shankar and Hollinger, 2007) and firm initiated and consumer initiated advertisements (Wiesel et al, 2011) respectively. This has implications on the role IDA impressions play in the context of high and low involvement consumers. If the consumer is actively searching, IDA's role is merely to act as a reminder. On the other hand if the consumer is passively surfing, IDA's role gets elevated of being the primary influencer.

A consumer is likely to be less involved if he or she is simply exposed to an IDA impression as such an exposure is involuntary in nature. As a result of such a passive IDA impression, a consumer is likely to have his or her curiosity triggered and a passing interest in the product generated by the initial few impressions. In this context a visitor is more likely to be looking to gather more knowledge and is akin to being in a learning situation. In a learning situation, a consumer is likely to process a message cursorily in the beginning and may only have a passing interest initially. In such a situation the visitor will need repeated exposures to the product message in order to absorb all the cues and information needed to evaluate the product which will help build his or her interest over time and eventually lead to a higher likelihood of a purchase. However, eventually a very high exposure frequency may lead to satiation and boredom and eventually lead to a decline in the effectiveness of IDA impressions in driving a purchase. Thus, we can hypothesize:

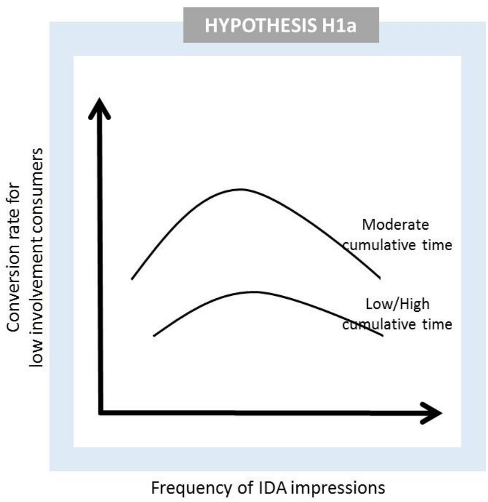
H1: In case of consumers with low involvement, the conversion rate will initially increase as the IDA exposure (impression) frequency increases, then reach a peak at a certain IDA impression frequency level, and eventually start to decline beyond a certain IDA impression frequency level.

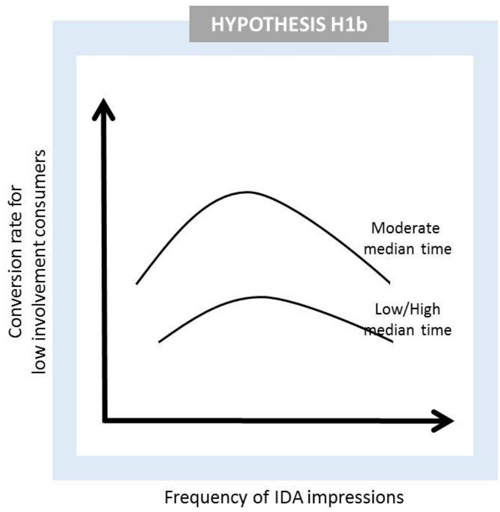


As the consumer is not actively looking to purchase the product being advertised, any rapid exposure to IDA impressions within a short period of time may be construed as irritation or may even convey some doubts about the product quality (Kirmani, 1997; Chatterjee et al, 2003). Instead it is more likely that a decision to purchase in case of a high involvement product is a longer process which will need detailed processing of all the information. The visitor is more likely to make a careful evaluation of the pros and cons and only make a decision after due consideration. Thus cues from advertising will be impactful only if there is more allowance for time in order for the consumer to cognitively process it, instead of being a source of irritation or interruption. Therefore IDA impressions should be spaced out across a longer period in order for restoration effects of the advertising to take place (Sawyer et al, 2009). This will allow gradual absorption of the message which may eventually lead to an increasing interest in the product. However, if the spacing between IDA impressions is spread out beyond a certain limit, the advertising may be less impactful due to a higher rate of forgetting (Braun and Moe, 2011). Therefore, as the consumer is in a learning situation, a high frequency of IDA impressions is required wherein the spacing between and across impressions is neither too less nor too high. Therefore we can hypothesize:

H1a: In case of consumers with low involvement, the conversion rate will initially increase as the IDA impression frequency increases, then reach a peak at a certain IDA advertising impression frequency level, and eventually start to decline beyond a certain IDA impression frequency level. The conversion rate will be highest for moderate cumulative time across IDA impressions and will be lower for higher or lower cumulative time across IDA impressions.

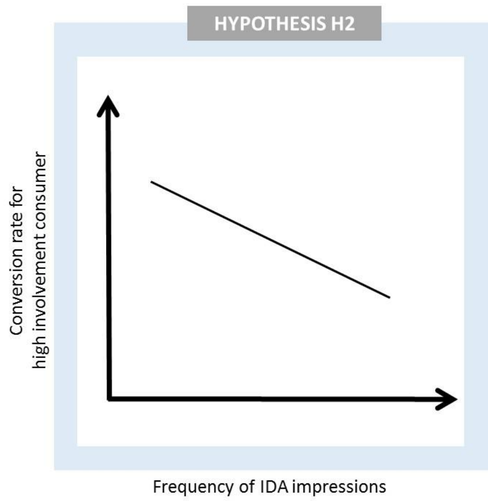
H1b: In case of consumers with low involvement, the conversion rate will initially increase as the IDA impressio) frequency increases, then reach a peak at a certain IDA impression frequency level, and eventually start to decline beyond a certain IDA impression frequency level. The conversion rate will be highest for moderate median time between IDA impressions and will be lower for higher or lower median time between IDA impressions.





A consumer is likely to be highly involved if he or she searches for the brand on a search engine (Danaher and Mullarkey, 2003) and clicks on the search advertisements. Such a consumer is likely to have a high level of interest in the product and brand and therefore is likely to have a higher level of motivation to eventually purchase the product. In such a situation it is more likely that a consumer is closer to making a purchase decision. In such a situation where consumers are actively searching and clicking on search results or paid search advertisements, the exposure to an IDA impression would act as a reminder for the consumer to take action, i.e. purchase the product he or she is searching for. In this case the role of IDA impressions is that of a reminder in much the way the recency theory postulates. Given that a consumer is close to making a purchase and therefore merely needs reminding, fewer IDA impressions will be required in order to trigger the consumer to make a purchase. Thus we can hypothesize:

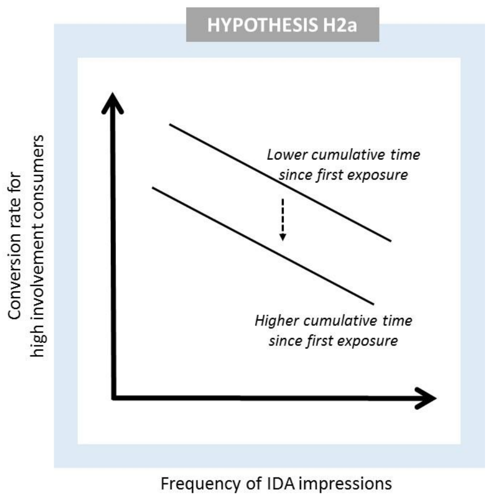
H2: In case of consumers with high involvement, the conversion rate will be higher at a lower IDA impression frequency level, and will decline as the IDA impression frequency level increases.

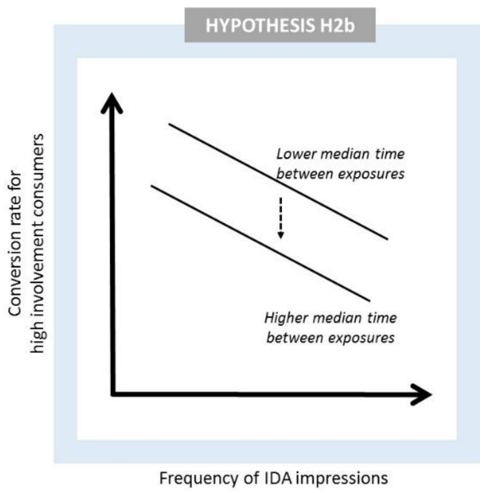


Moreover, since the consumer is close to a purchase decision, it is more likely that he or she makes a purchase sooner rather than later. Therefore the IDA impressions should occur within a relatively shorter time interval in order for the consumer to make a purchase. Also, each of these impressions should occur within a short interval of each other. Therefore we can hypothesize:

H2a: In case of consumers with high involvement, the conversion rate will be higher at lower IDA impression frequency levels, and will decline as the IDA impression frequency level increases. The conversion rate will be highest for lower cumulative time across IDA impressions and will decrease as the cumulative time across IDA impressions increases.

H2b: In case of consumers with high involvement, the conversion rate will be higher at lower IDA impression frequency levels, and will decline as the IDA impression frequency level increases. The conversion rate will be highest for lower median time between IDA impressions and will decrease as the median time between IDA impressions increases.





IDA impression frequency and brand familiarity

The brand is an integrated resort located in Singapore with many products, such as attractions, events and hotels, all co-located in the same geographical area. The consumers for the brand in this study are either local tourists, i.e. residents of Singapore, or foreign tourists who reside in markets outside of Singapore. Naturally, consumers residing in Singapore are geographically closer to the destination brand than the consumers who are residing in other countries outside of Singapore. Sociological researchers such as Griswold and Wright (2004) have suggested that geographical distances help shape unique cultural identities across geographical locations. Their analysis suggests that consumer's knowledge and familiarity will be higher for a geographical location which is their place of residence versus a location that is not their place of residence. Research on tourism has highlighted the different levels of familiarity amongst local tourists, i.e. residents, and foreign tourists vis-à-vis a destination. Generally most such studies suggest a higher level of familiarity for a destination amongst local tourists than amongst foreign tourists (Massara and Severino, 2013). Research in the tourism sector highlights the fact that foreign tourists tend to remember fewer aspects of a destination compared to residents (Walmsley, 1992; Young, 1999).

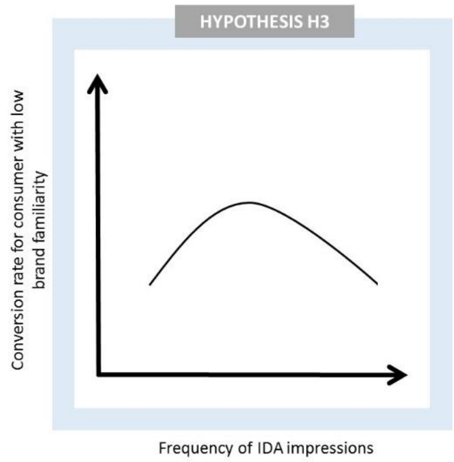
Some of the reasons for the lower familiarity amongst foreign tourists is lower cultural affinity (Prentice and Andersen, 2006) and higher costs associated with overseas travel that reduces the number of visits and repeat visits by foreign tourists to a destination (Culpan, 1987), which in turn reduces the level of familiarity (Prentice and Andersen, 2006). Despite the growth of internet, the psychological gap between consumers and brands continues to be perpetuated due to geographical separation (Edwards et al, 2009). An analysis of the search volume for 2013 for the brand under study, using Google keyword tool, shows that the number of information searches for the brand in Singapore (the home market) exceeds the number of searches in non-Singapore markets as seen in Table 3 below. As information searches help to improve brand familiarity for a destination (Ho et al, 2012), the lower brand related information searches amongst foreign tourists suggests lower brand familiarity amongst foreign tourists versus local tourists.

Table 3: Total volume of keywords related to brand in home market (i.e. Singapore) and non-home market (i.e. Malaysia). Source: Google Adwords

Singapore			Malaysia		
S No.	Keyword	Searches	S No.	Keyword	Searches
1	universal studios singapore	49,500	1	universal studio singapore	22,200
2	sentosa	33,100	2	universal studios singapore	12,100
3	adventure cove	22,200	3	christmas	12,100
4	S.E.A Aquarium	18,100	4	uss singapore	5,400
5	sea aquarium	18,100	5	sentosa	4,400
6	resort world sentosa	14,800	6	universal studios	3,600
7	rws	14,800	7	peter pan	3,600
8	trick eye museum	14,800	8	resort world sentosa	3,600
9	things to do in singapore	12,100	9	adventure cove	3,600
10	uss	9,900	10	uss	3,600
11	christmas	6,600	11	aquarium	2,400
12	universal studio singapore	6,600	12	universal studio	2,400
13	sentosa hotels	6,600	13	S.E.A Aquarium	2,400
14	uss singapore	6,600	14	sea aquarium	2,400
15	underwater world singapore	6,600	15	hello kitty land	2,400
16	resorts world sentosa	5,400	16	trick eye museum	2,400
17	trick eye museum singapore	5,400	17	underwater world singapore	1,900
18	universal studios	4,400	18	things to do in singapore	1,600
.....			.....		
	All keywords	380,620		All keywords	142,630

A consumer with low brand familiarity needs to learn about the brand, before he or she can make a decision to purchase it. Various researches on advertising exposure frequency have concluded that a higher level of frequency of advertising exposures are necessary to drive a response in situations where advertising's role is to impart learning about a brand – a situation that would occur when a consumer has lower familiarity with a brand (Tellis 1988; Tellis, 1997). In such a situation, the wear-in of the initial IDA impressions would gradually increase as the frequency of IDA impressions increases. It is likely to reach a peak at a certain level of frequency and eventually decline after that level as wear-out of IDA impressions becomes higher than the wear-in of IDA impressions. Therefore we can hypothesize:

H3: In case of consumers with low brand familiarity (i.e. those residing in home market), the conversion rate will initially increase as the IDA impression frequency increases, then reach a peak at a certain IDA impression frequency level, and eventually start to decline beyond a certain IDA impression frequency level.

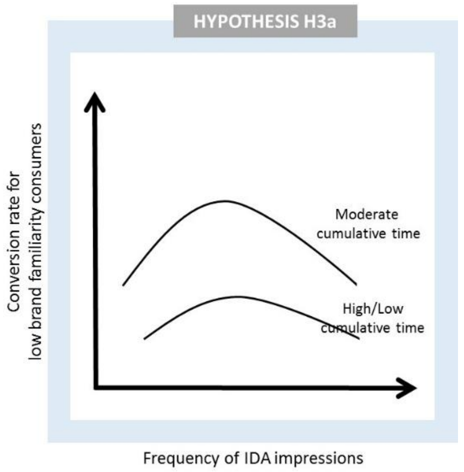


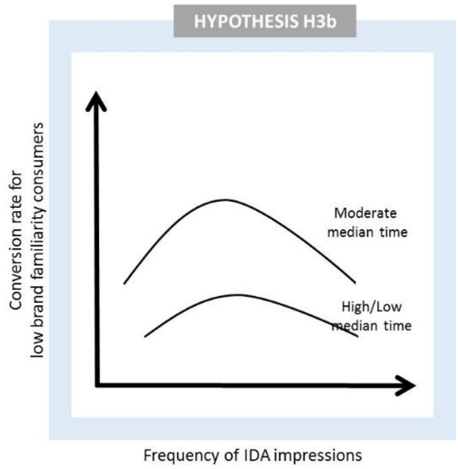
As is the case with consumers with low involvement, consumers with low brand familiarity will require moderate spacing between IDA impressions in order to assimilate the message and act upon it positively. A spacing between and across IDA impressions that is too less is likely to prevent a complete wear-in of the IDA impression to occur. On the other hand too high a spacing between and across

IDA impressions may lead to forgetting of the message thus leading to an almost complete decay of the memories of the advertising impressions. Therefore, we can hypothesize:

H3a: In case of consumers with low brand familiarity (i.e. those residing in home market), the conversion rate will initially increase as the IDA impression frequency increases, then reach a peak at a certain IDA impression frequency level, and eventually start to decline beyond a certain IDA impression frequency level. The conversion rate will be highest for moderate cumulative time across IDA impressions and will be lower for higher or lower cumulative time across IDA impressions.

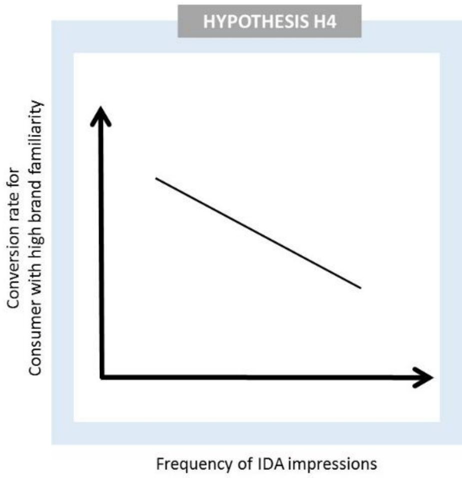
H3b: In case of consumers with low brand familiarity (i.e. those residing in home market), the conversion rate will initially increase as the IDA impression frequency increases, then reach a peak at a certain IDA impression frequency level, and eventually start to decline beyond a certain IDA impression frequency level. The conversion rate will be highest for moderate median time between IDA impressions and will be lower for higher or lower median time between IDA impressions.





Conversely in case of consumers with high brand familiarity, the frequency of advertising exposures required to drive effectiveness is lower (Ostrow, 1984; Ephron, 1995). Advertising exposures are more effective amongst consumers who reside in close geographical proximity to the product than those who do not reside in close geographical proximity (Johnson et al, 2014). Some have even suggested that in such cases even a single exposure will be effective as has been espoused by the recency theorists (Ephron, 1995). Thus, we can hypothesize:

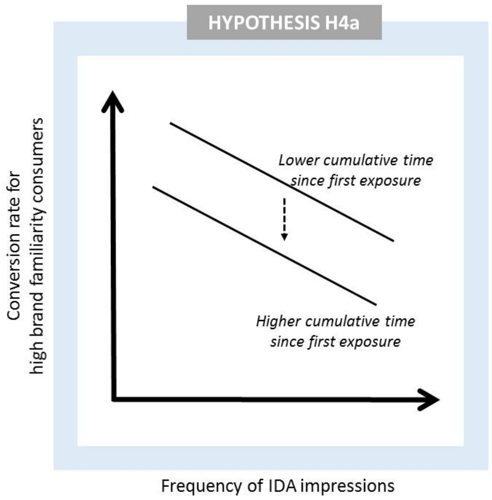
H4: In case of consumers with high brand familiarity (i.e. those residing in home market), the conversion rate will be higher at lower IDA impression frequency levels, and will decline as the IDA impression frequency level increases.

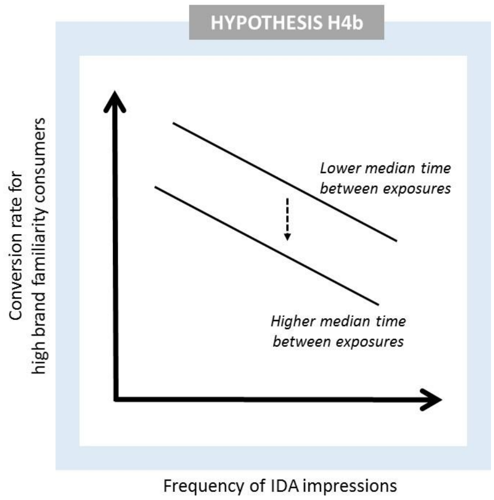


Moreover, since a consumer has higher brand familiarity, it is more likely that the wear-in of the advertising message is extremely fast. Therefore it is likely that exposure to a few IDA impressions within a short time interval should lead to a purchase. Therefore we can hypothesize:

H4a: In case of consumers with high brand familiarity (i.e. those residing in home market), the conversion rate will be higher at lower IDA impression frequency levels, and will decline as the IDA impression frequency level increases. The conversion rate will be highest for lower cumulative time across IDA impressions and will decrease as the cumulative time across IDA impressions increases.

H4b: In case of consumers with high brand familiarity (i.e. those residing in home market), the conversion rate will be higher at lower IDA impression frequency levels, and will decline as the IDA impression frequency level increases. The conversion rate will be highest for lower median time between IDA impressions and will be decrease as the median time between IDA impressions increases.


HYPOTHESIS H4a
Conversion rate for high brand familiarity consumers
Lower cumulative time since first exposure
Higher cumulative time since first exposure
Frequency of IDA impressions


HYPOTHESIS H4b
Conversion rate for high brand familiarity consumers
Lower median time between exposures
Higher median time between exposures
Frequency of IDA impressions

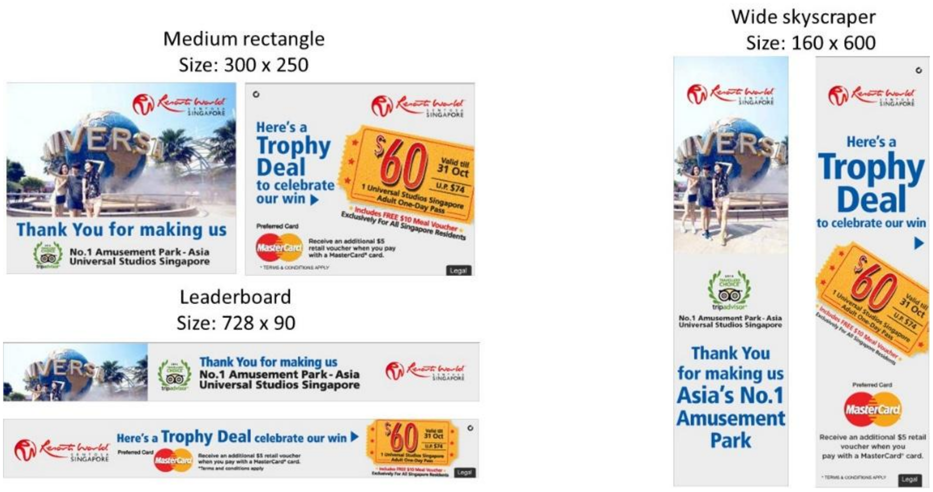
DATA

Data source

Disaggregated advertising log data was obtained for an integrated resort based in Singapore. The integrated resort's IDA campaigns were for ticketed attractions that are located within the resort. These ticketed attractions include a theme park, an aquarium and a water-park. Some campaigns advertised just one product, whilst some other campaigns advertised a bundle of products. The advertising log data was for thirteen IDA campaigns that ran between the dates 1st August, 2014 to 31st January, 2015. The shortest campaign duration was eleven days whilst the longest campaign duration was 151 days. The advertising log data consisted of all IDA impressions, search clicks, website visits and online purchases associated with the thirteen campaigns.

All the thirteen campaigns were similar in terms of advertising creative, i.e. all had a similar mix of creative messages, sizes and formats. All the campaigns had creatives that included a brand component and a direct response component. The brand component consisted of a visual of the product being advertised, i.e. either the theme park, aquarium or water-park, and the direct response component consisted of the price of the product/product-offer being advertised. A sample of the advertisements for one of the campaigns is show in Image 3 below:

Image 3: Sample campaign advertisements



Data extraction

The data from the ad-servers was extracted from the ad-server account of a large international advertising agency's ad-server account. The advertising agency manages all the IDA campaigns for this brand. Each day, the ad-server provides three files that contain IDA impression, activity, and click data. The files are named 'impression', 'activity', and 'clicks' respectively and contain data in 'text' format. The structure of these files and the detailed description of the variables in each of the three files is provided in Appendix A and Appendix B respectively.

The common identifier across all the three files is the field 'User ID'. This 'User ID' is a cookie ID that is generated by the ad-server and resides in the user's web browser. Thus each cookie ID represents a unique user. This is in line with other IDA based researches that too make a similar assumption that a unique cookie is a unique user (Manchanda, et al, 2006). Each time the user is exposed to an IDA impression, clicks on a paid search advertisement, visits the advertiser's website or purchases online on the website, the action is stored as a line in either the 'impression' (for IDA impressions), 'activity' (for website visits or online purchases) or 'clicks' (for clicks on paid search advertisements) file. Each day approximately 1.5 million lines are generated. Data was extracted using a customized code written in R. In total there were 161.2 million unique cookies which were exposed to 770.8 million IDA impressions in the data-set.

The data-set was checked for the incidence of cookie deletion to restrict a potential issue of multiple unique cookies being generated for the same unique user. This can occur if a user deletes the cookie cache in his or her web browser. The number of unique cookies was compared across the full campaign period, a four-week period and a two-week period as per a method suggested by Woodman (2012). The increase in the number of unique cookies from a two-week period to the entire campaign was on an average just 17.6%. This is considerably lower than an earlier research that showed a 31% increase in unique cookies over a thirty days (Abraham et al, 2007). The lower incidence of new cookies in the data-set for this study compared to the 2007 study suggests a gradual improvement in the acceptance of cookies by internet users. Perhaps this is not surprising as more and more users enjoy the benefits of keeping cookies in their browsers such as reduction in time and effort required to fill in online forms or undertake online transactions. Further, the default setting for most browsers is set to keep the cookies intact. Hence, given the lower incidence of cookie deletion, the analysis utilized the data for the entire campaign period rather than to truncate the data-set to a shorter two or four week period which has been the norm for some of the other researches such as the one by Manchanda et al (2006).

The total size of the data-set was approximately 254 gigabytes. Most other researches with access to such large data-sets are usually confined to large publishers such as Google and Yahoo! However, such researches' data-sets consist of IDA impressions of just one website such as the one undertaken by Johnson et al (2014) which was based on IDA impressions that appeared only on Yahoo! On the other hand non-publisher led studies are perforce limited to smaller data-sets. Therefore, access to such a large data-set provided a unique opportunity for this study.

Data preparation

The first step in the data preparation was to construct the consumer journey for every consumer (identified as a unique cookie). This was done by stringing together chronologically every IDA impression, website visit, paid search advertisement click and an online purchase for every day throughout the period of every campaign. Construction of a consumer journey commenced from the time the first IDA impression associated with a campaign appeared for a unique cookie. The earliest possible date for a consumer journey for a campaign was the commencement date for that campaign. The last possible date for a consumer journey was either the campaign end date or when an online conversion, i.e. purchase, associated with a cookie occurred. The online purchase associated with a cookie was checked till thirty days beyond the campaign end date. The shortest consumer journey consisted of one IDA impression whilst the longest consumer journey consisted of 30,629 impressions.

Whilst constructing the consumer journey, multiple IDA impressions in one second for a single cookie for a single browser on a single publisher was removed altogether. This method mitigated somewhat the issue of ‘non-viewable’ IDA impressions. Non-viewable impressions are those IDA impressions that do not load completely for even one second (Flosi et al, 2013). 15% of IDA impressions were thus removed from the original data-set.

Once every consumer journey was constructed, the number of IDA impressions, i.e. the IDA impression frequency for every consumer journey was counted. IDA impressions for every consumer journey were classified as premium or mass. All IDA impressions bought directly from publishers was classified as premium impressions. Such IDA impressions tend to be more prominently displayed, appear in more congruent and/or prestigious websites and are usually more expensive than mass impressions. Mass IDA impressions are usually purchased via ad-networks. Median time between IDA impressions and the cumulative time between the first and last IDA impression for every consumer journey was calculated. An ‘R’ software code was deployed to construct the consumer journey and thereafter to tabulate the data. This was done for all the significant campaigns during the six-month period, 1st August 2014 to 31st January, 2015. Each full iteration took approximately 72 hours and was done using a code written in R. Singapore Management University’s High Performance Computer Centre’s facilities were used to prepare the data-set. The tabulation format is shown in Appendix C.

Upon tabulation, the data-set was further tightened to consumer journeys with a maximum frequency of 250 IDA impressions. 99.9% of users, i.e. cookies, 87.3% of IDA impressions and 99% of conversions, i.e. online purchases, were accounted for by users who were exposed up to a frequency of 250 IDA impressions. As there was a presence of heteroskedasticity for conversions in the higher frequencies, the data was re-tabulated from discrete frequencies to categorical frequency intervals of ten starting with a frequency interval of 1-10 till a frequency interval of 241-250 IDA impressions. Finally, data for two out of the thirteen campaigns was excluded as the data for these campaigns was truncated and therefore very sparse. These two campaigns ran for a period of two weeks or less in the month of January, 2015.

Another set of tabulation was done to cross-tabulate the count of consumer journeys by different intervals of cumulative time as well as different intervals of median time. The ensuing tabulation resulted in two matrices. The first matrix consisted of IDA impression frequency ranges x cumulative time intervals across the first and last IDA impression. Frequencies were categorized into intervals of ten, starting from 1-10….till 241-250. Cumulative time was categorized into intervals of ten days starting from 1-10 days....till 90+ days. The second matrix consisted of IDA impression frequency ranges x median time intervals between successive IDA impressions. Frequencies were categorized in intervals of ten, starting from 1-10….till 241-250. Median time was categorized into intervals of six hours starting from 0-6 hours to 42-48 hours.

MODEL

A persistent issue that impacts researches that seek to determine advertising response curves for IDA impressions, especially in cases where the response variable is a website visit or a purchase, has been the extremely small likelihood of successes compared to the total number of IDA impressions. Lee and Briley (2005) left the issue unresolved, and as a result perhaps not surprisingly, most of the findings from their study were insignificant. Manchanda et al (2006) used a semi-parametric survival function to model the relationship between IDA impressions and online purchases. However, in order to do that the researchers only considered those consumers who had made at least one online purchase during a thirteen week period while being exposed to IDA impressions, and ignored those consumers who did not make any online purchases during this period. Therefore even though the model was based on a sub-set of repeat consumers, it is important to note that the percentage of successful IDA impressions, i.e. those that resulted in a purchase, to the total IDA impressions that the consumers were exposed to, was only 14.3%. This clearly suggested that an inclusion of consumers who did not purchase during the entire thirteen week period (if it had been possible) would have resulted in a miniscule conversion rate that would have been extremely difficult to model with the function. Others such as Danaher (2007; 2014) developed a multivariate negative binomial distribution (MNBD) model to model distribution of exposures/ impressions. However, the model does not address distribution of website visits or online purchases, a metric more pertinent to our study. Therefore, given these issues, this study sought to explore an alternative method to suitably model the effect of IDA impression frequency to online purchases.

Most of the work done on developing and understanding advertising response curves in relation to frequency of advertising exposures have concluded that the shape of the advertising response curves is mostly non-linear. Researchers have either found the advertising response curves in traditional media to be ‘S-shaped’ (Rao and Miller, 1975; Metwally; 1980) or diminishing concave shaped (Simon and Arndt, 1980; Jones, 1995a; 1995b).

In the case of IDA too, much of the evidence on advertising response curves to IDA impressions showed the prevalence of the downward concave shaped curve (Broussard, 2000; Chatterjee et al, 2003; Manchanda et al, 2006). Given the possibility that most advertising response curves for IDA impression frequency supported the diminishing curve shape, Lee and Briley (2005) tested a polynomial model of degree two whilst proposing a suitable model to show the effectiveness of IDA impressions in driving brand message recall. Their model showed an improvement over another model which was linear.

Findings from a recent research done by Nottorf (2013), raised the possibility of a polynomial model of a higher degree than two being a better fit with IDA impression data. The research highlighted evidence that suggested the existence of a small but unique consumer segment, termed as the ‘susceptible consumer type’ who is more likely to be impacted by an IDA impression than an average consumer. This consumer is more likely to respond after repeated exposures to IDA impressions, and the likelihood of such a response actually increases over time and over higher frequency of IDA impressions. This behaviour is independent of the nature of the consumer such as whether he or she is high or low involvement. A possible reason for the presence of such as segment would be the nature of the internet itself that has spawned new types of behaviours amongst consumers including the emergence of a consumer who is more prone to responding to IDA impressions over time. The possibility of such a behaviour emerging is high in the data-set for this study given its duration (the longest campaign is for 151 days) and the fact that the impact of IDA impression frequencies of up to 250 are being analysed. Therefore, the model developed for analysis in the study is a polynomial model of the degree three.

Variables and their operationalization

Dependent variable

The dependent variable of the model is *Conversion Rate*. The conversion rate is calculated as the ratio of the number of users, i.e. unique cookies, who converted, i.e. purchased online, to the total number of users, i.e. unique cookies, exposed to IDA impressions.

$$\text{Conversion Rate} = \frac{\text{[Total number of converted consumers (cookies)]}}{\text{[Total number of consumers (cookies)]}}$$

As the conversion rate will range between zero and one, it was log transformed. In instances where the conversion rate was zero, a very small number i.e. 0.0000001 was added before undertaking the log transformation. Thus conversion rate was included in the model as a *Log (Conversion Rate)* (CONVRATE_LN). This is line with other researches that too have employed such a log transformation (Lee and Briley, 2005).

Independent variable

IDA impression *Frequency* (FREQ) is the independent variable. Given the hypothesized non-linear shape of the advertising response curve, *Frequency*^{2} (FREQ^2) and *Frequency*^{3} (FREQ^3) were also used as independent variables. The frequency variable is in the model as a count of the number of consumers (cookies) at each of the twenty five frequency intervals starting from a frequency interval of 1-10, up to a frequency interval of 241 – 250. The frequency interval 1-10 interval is coded as ‘0’, and the rest are coded from ‘1’ (for 11-20) to all the way to ‘24’ (for 241-250). Given the deployment of the polynomial model degree three, the expected sign of the coefficient for *Frequency* was positive, for *Frequency*^{2} was negative and *Frequency*^{3} was positive.

Moderator variables

Four moderator variables have been factored in. They are:

Consumer Involvement (INVOLV): The operationalization of involvement was done by the incidence or absence of a search click on a consumer journey. A consumer has *high involvement* if one or more search clicks are present in the consumer journey. Such a consumer will have a mix of search clicks and IDA impressions in his or her consumer journey. This is consistent with the widespread acceptance that searching on a search engine is a manifestation of a consumer's higher level of involvement (Ha, 2008; Shankar and Hollinger, 2007; Spilker-Attig and Brettel, 2010; Wiesel et al, 2011). Conversely, if the consumer does not have any search click on his or her consumer journey then it is a manifestation of a consumer with *low involvement*. Consumer involvement was included in the model as a dummy variable in which low consumer involvement = 1 and high consumer involvement = 0. The sign for the co-efficient of *consumer involvement* is expected to be negative as lower consumer involvement is expected to lead to a lower incidence of purchases and hence a lower conversion rate.

Brand familiarity (FAMILIAR): The operationalization of brand familiarity was done on the basis of the geographical location of the consumer (cookie). A consumer is deemed to have *low brand familiarity* if the country in which the consumer (cookie) resides in a location outside of the home market, i.e. Singapore. Conversely a consumer is deemed to have *high brand familiarity* if a consumer (cookie) resides in the same market as that of the destination, i.e. Singapore. Consumer's brand familiarity was included in the model as a dummy variable in which low brand familiarity = 1 and high brand familiarity = 0. The sign for the co-efficient of *brand familiarity* was expected to be negative as lower brand familiarity is expected to lead to a lower incidence of purchases and hence a lower conversion rate.

Cumulative time (CUMTIME) across IDA impressions is the total time across the first and last IDA impression in a consumer journey. Cumulative time was included in the model as a continuous variable and is measured in seconds. There was no hypothesized sign for the coefficient of cumulative time.

Median time (MEDTIME) between IDA impressions is the intra-impression time in between two consecutive IDA impressions in a consumer journey. Median time was included in the model as a continuous variable and is measured in seconds. There was no hypothesized sign for the coefficient of median time.

Interaction terms

The following interaction terms were included in the model:

- *Consumer Involvement x Frequency* (INVOLV*FREQ)
- *Consumer Involvement x Frequency*^{2} (INVOLV*(FREQ^2))
- *Brand Familiar x Frequency* (FAMILIAR*FREQ)
- *Brand Familiar x Frequency*^{2} (FAMILIAR*(FREQ^2))
- *Consumer Involvement x Cumulative Time* (INVOLV*CUMTIME)
- *Brand Familiarity x Cumulative Time* (FAMILIAR*CUMTIME)
- *Consumer Involvement x Median Time* (INVOLV*MEDTIME)
- *Brand Familiarity x Median Time* (FAMILIARITY*MEDTIME)

Control variables

The following two control variables were incorporated in the model:

Premium impressions (PREM) is the share of premium IDA impressions compared to total IDA impressions at each frequency level. IDA impressions that appear on websites that are more congruent to the product being advertised or websites that are considered to be more prestigious have been classified as premium for purposes of this research. As the IDA impressions are for a travel and leisure category product, travel and leisure websites such as TripAdvisor.com will have higher congruency. Websites such as Yahoo! that command higher consumer traffic in the markets which the campaigns appeared in are seen as being more dominant. Therefore IDA impressions in such highly congruent or dominant websites were considered as being premium. The IDA impressions on the remainder of the websites were considered as mass. As IDA impressions on premium media vehicles are likely to be more impactful as they are seen by consumers as being more credible and attention grabbing (Shamdasani et al, 2001; Rossiter and Danaher, 1998 pp 30-31) such premium IDA impressions are expected to have a positive impact on conversion rate. Therefore the sign of the co-efficient for share of *premium* impressions was expected to be positive.

IDA impressions for campaigns that targeted the consumers with ostensible offers for the festive season were classified as *festive* (FESTIV). Such campaigns were specifically developed to target consumers during the Christmas and New Year holiday season. As more consumers are likely to visit and therefore purchase products in the travel and leisure category during the festive season, the sign of the co-efficient of *festive* was expected to be positive. Festive campaigns were coded as ‘1’, whereas the balance campaigns were coded as ‘0’.

RESULTS

The results of the model are given below in Table 4.

Table 4: Results of the overall model

Sample: 1 550
Included observations: 550

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.235280	1.407739	-0.877492	0.3806
FREQ	0.626749	0.271878	2.305257	0.0215
FREQ^2	-0.080622	0.022172	-3.636303	0.0003
FREQ^3	0.002234	0.000572	3.907765	0.0001
INVOLV	-6.045075	1.063185	-5.685817	0.0000
FAMILIAR	-2.783802	1.322740	-2.104572	0.0358
INVOLV*FREQ	0.310633	0.188849	1.644874	0.1006
INVOLV*(FREQ^2)	-0.010813	0.007328	-1.475650	0.1406
FAMILIAR*FREQ	0.019271	0.192132	0.100303	0.9201
FAMILIAR*(FREQ^2)	-0.008587	0.007408	-1.159098	0.2469
CUMTIME	-2.38E-07	2.51E-07	-0.948372	0.3434
MEDTIME	-6.92E-06	1.05E-05	-0.656694	0.5117
INVOLV*CUMTIME	3.82E-07	1.32E-07	2.903263	0.0038
FAMILIAR*CUMTIME	-1.92E-09	2.56E-07	-0.007490	0.9940
INVOLV*MEDTIME	-3.39E-06	6.38E-06	-0.531783	0.5951
FAMILIAR*MEDTIME	9.69E-06	1.10E-05	0.882518	0.3779
PREM	2.397931	0.837903	2.861823	0.0044
FESTIVE	-2.804046	0.785492	-3.569794	0.0004

R-squared	0.391024	Mean dependent var	-6.471329
Adjusted R-squared	0.371564	S.D. dependent var	4.665091
S.E. of regression	3.698202	Akaike info criterion	5.485751
Sum squared resid	7276.005	Schwarz criterion	5.626802
Log likelihood	-1490.581	Hannan-Quinn criter.	5.540871
F-statistic	20.09395	Durbin-Watson stat	1.757966
Prob(F-statistic)	0.000000		

The model fitted the data-set using OLS. The overall fit of the overall was quite strong with an adjusted $R^2 = 0.37$. The coefficient of *frequency* (FREQ) is significant at the 95% confidence level while the coefficients of *frequency*^{2} (FREQ^2) and *frequency*^{3} (FREQ^3) are significant at the 99% confidence level. Also, all the signs of the coefficients are in the right direction.

Amongst the moderator variables, the co-efficient of *involvement* (INVOLV) was significant at the 99% confidence level and the negative sign of the co-efficient was in the right direction. The coefficient of *familiarity* (FAMILIAR) was significant at the 95% confidence level and the negative sign of the coefficient was in the right direction. The variables, *cumulative time* (CUMTIME) and median time (MEDTIME) are not significant. The negative sign of the co-efficient suggests that for the IDA impressions analysed, there was a negative relationship between intra-impression time and conversion rate.

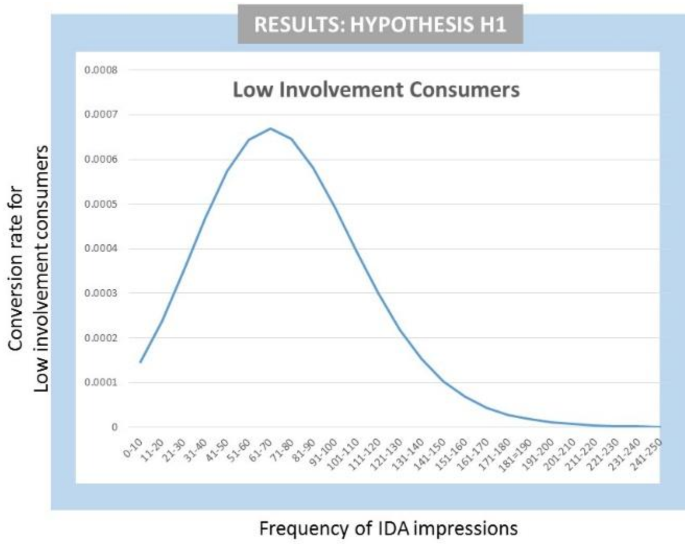
Amongst the interaction terms, most were not significant with the exception of consumer involvement x cumulative time (INVOLV*CUMTIME). The sign for the co-efficient was positive thus suggesting that lower consumer involvement interacts positively with higher cumulative time across the first and last IDA impressions in a consumer journey in order to drive conversion rate.

The two control variables, premium (PREM) and festive (FESTIV) have significant results. Premium IDA impressions seem to have a positive impact on conversion rate, with the co-efficient being significant at the 99% confidence level. The other control variable, festive is also significant, but the sign is negative. This is somewhat a surprise, as it is against the expected positive sign.

Summary of findings: Main Effects

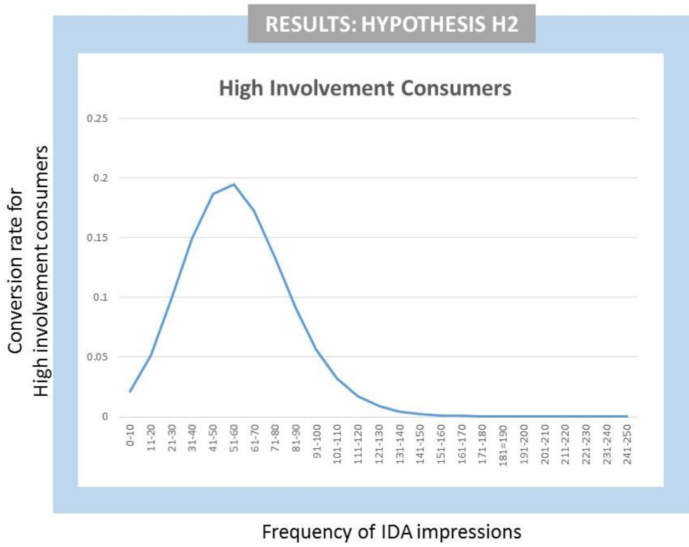
Low consumer involvement and IDA impression frequency

For low involvement consumers, the conversion rate increases as the IDA impression frequency increases, and reaches a peak at the frequency range of 61-70. Thereafter for higher IDA impression frequency levels the conversion rate declines. Thus, *hypothesis H1 is supported.*



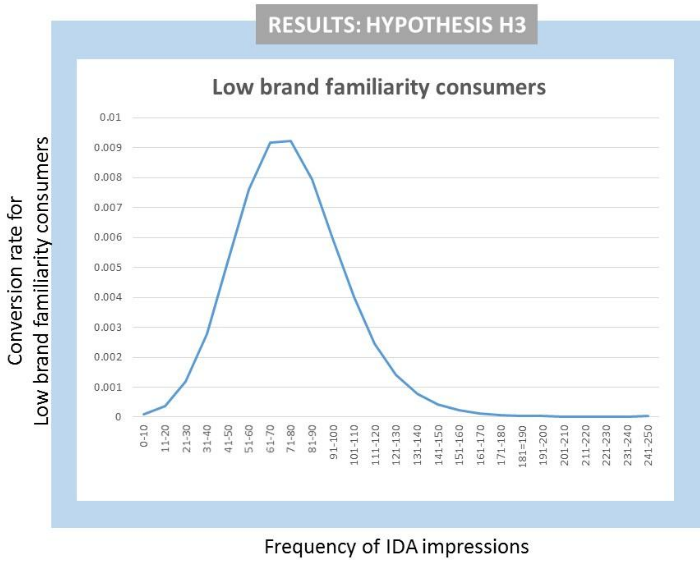
High consumer involvement and IDA impression frequency

For high involvement consumers, the conversion rate increases as the IDA impression frequency increases, and reaches a peak at the frequency range of 51-60. Thereafter for higher IDA impression frequency levels the conversion rate declines. However, this finding does not support the downward sloping curve as was hypothesized. Thus *hypothesis H2 is not supported.*



Low brand familiarity and IDA impression frequency

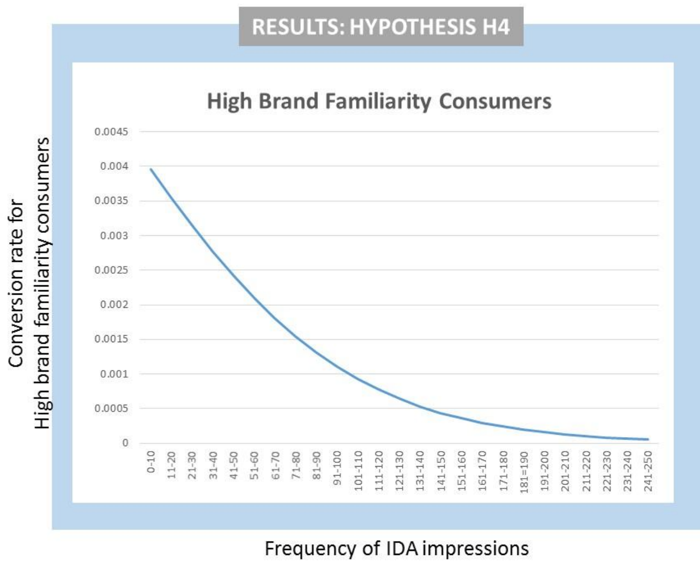
For consumers with low brand familiarity, the conversion rate increases as the IDA impression frequency increases, and reaches a peak at the frequency range of 71-80. Thereafter for higher



IDA impression frequency levels the conversion rate declines. Thus *hypothesis H3 is supported.*

High brand familiarity and IDA impression frequency

For consumers with high brand familiarity, the conversion rate decreases as the IDA impression frequency range increases. Therefore the advertising response curve is downward



sloping curve. Thus *hypothesis H4 is supported.*

Overall, three out of the four hypotheses are supported from the results of the findings.

Summary of findings: Moderating Effects

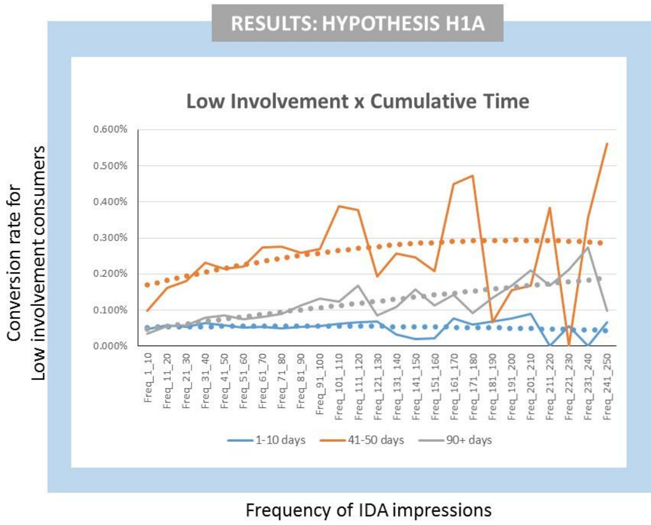
To understand the impact of IDA impression frequency on conversion rate by keeping both cumulative time across IDA impressions and median time between impressions constant, two matrices were generated.

The first matrix consisted of frequency ranges (The frequencies were categorized into intervals of ten, starting from 1-10….till 241-250) x cumulative time intervals (Cumulative time was categorized into intervals of ten days starting from zero days, 1-10 days....till 90+ days). This resulted in 11 x 250 = 2750 cells. Given the high number of cells the data was sparse in a majority of the cells. A similar situation of sparse data arose in the second matrix of frequency ranges and median time. The second matrix consisted of frequency ranges (The frequencies were categorized in intervals of ten, starting from 1-10….till 241-250) x median time intervals (Median time was categorized into intervals of six hours starting from zero days to ten days). In this case there were 10500 cells. Given the large number of cells in the matrix no modelling was undertaken. Instead, the data was simply tabulated, and the highlights are presented.

Also, as the hypothesis for the main effects of IDA impression frequency for consumers with high involvement was not supported, hypothesis for the moderating effects of cumulative time and median time are not presented.

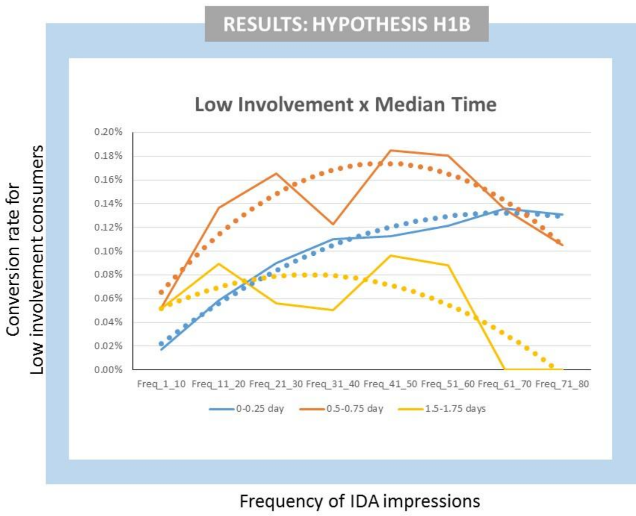
Low consumer involvement x cumulative time

The conversion rate is highest at moderate cumulative time (41-50 days) than it is for higher (81-90 days) or lower cumulative time (1-10 days). Thus *hypothesis H1a is supported*.



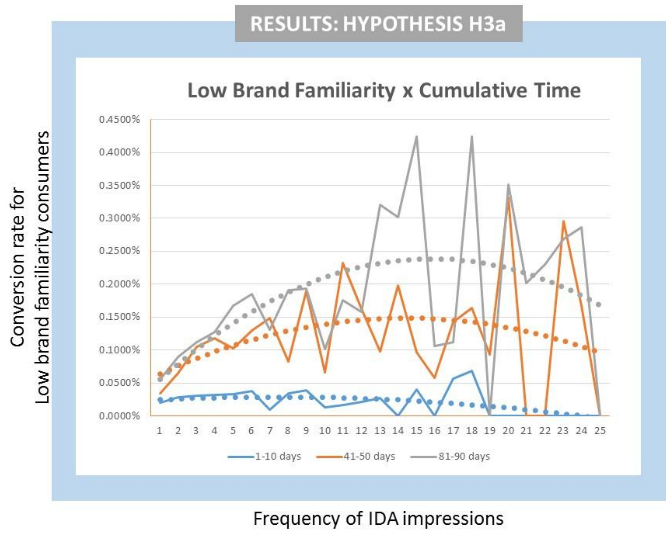
Low consumer involvement x median time

The conversion rate is highest at moderate median time (12-18 hours) compared to higher (36-42 hours) or lower median time (0-6 hours). Thus *hypothesis H1b is supported*.



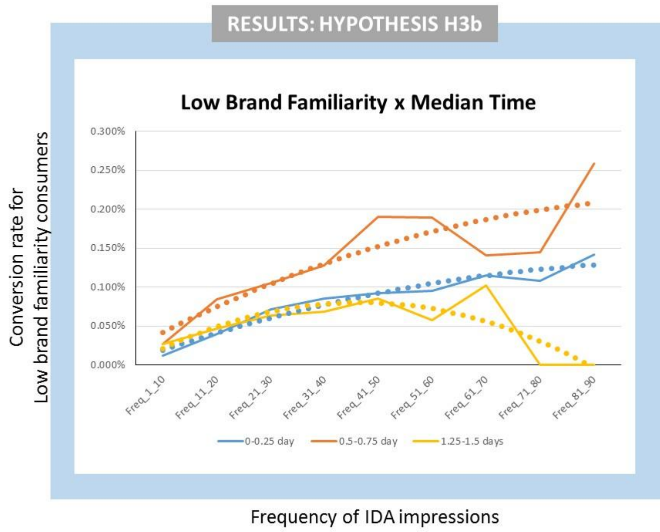
Low brand familiarity x cumulative time

The conversion rate is lowest at low cumulative time (1-10 days). Conversion rate is highest for highest cumulative time (81-90 days) which is slightly higher than for moderate cumulative time (41-50 days). Thus *hypothesis H3a is partly supported.*



Low brand familiarity x median time

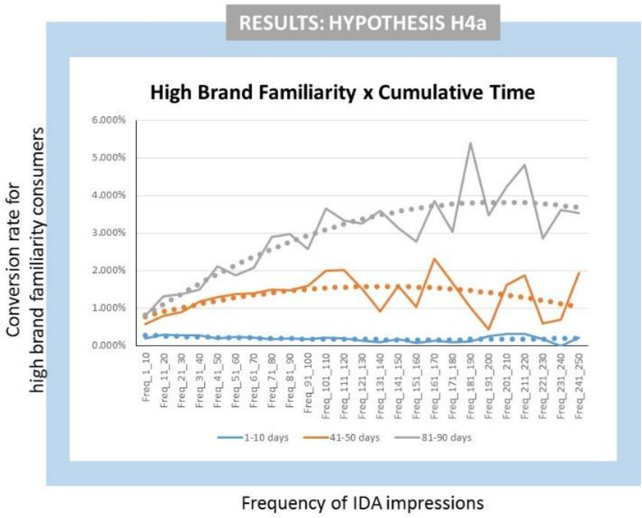
The conversion rate is highest at moderate median time (12-18 hours) compared to higher (36-42 hours) or lower median time (0-6 hours). Thus *hypothesis H3b is supported.*



High brand familiarity x cumulative time

The conversion rate increases as the cumulative time increases (opposite from the order hypothesized).

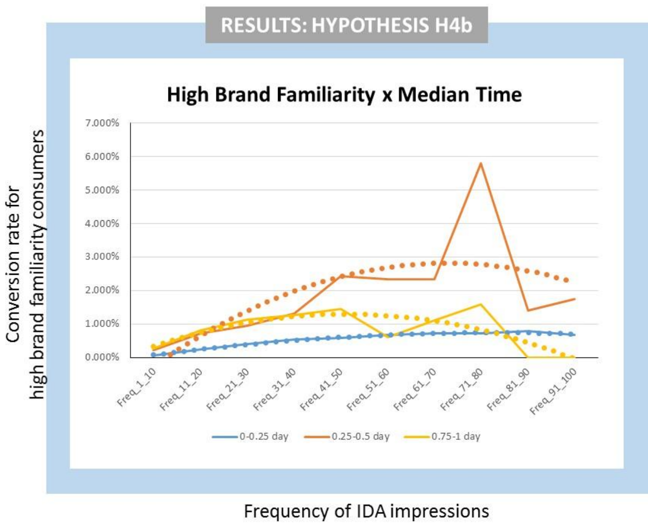
Thus *hypothesis H4a is not supported*.



High brand familiarity x median time

At lower frequency levels (1-10) conversion rate is highest at moderate median time (6-12 hours) compared to that of moderate and higher median time.

Thus *hypothesis H4b is supported*.



DISCUSSION

Main effects

Higher peak IDA impression frequency level than conventionally accepted

The higher levels of frequency at which conversion rates seem to peak in this study for consumers with low involvement (61-70) and high involvement (51-60) as well as consumers with low brand familiarity (71-80), is considerably higher than optimal frequency level recommendations from studies that were based on advertising on traditional media such as television. Most of the effective frequency studies based on traditional media such as those by Krugman (1972), Naples (1979) and Vakratsas and Ambler (1999) supported an advertising exposure frequency that rarely exceeded three.

However, findings from this study are in line with recent studies on IDA impressions that seem to suggest that a higher level of advertising exposure frequency may be quite the norm for IDA. Dreze and Hussherr (2003) showed in their experiment that repetition of IDA impressions of up to six was effective. The experiment did not test a frequency of more than six. Lee and Briley (2005) too showed an increase in advertising response albeit at a diminishing rate till the maximum frequency exposure that was tested which was thirty. Taylor et al (2013) compared the average frequency that drove sales in the FMG category for both television and IDA. The average frequency for television was 3.4 while that for IDA was 11. Finally, Johnson et al (2014) who measured the effect of multiple frequency of IDA impressions on Yahoo! showed that even at a frequency of 50, the advertising response was still increasing. Thus the findings from our study that relatively higher advertising exposure frequency levels are required on IDA compared to advertising exposures on traditional media, seem to align with the findings of other recent studies on IDA.

Linked to higher frequency levels, is a related trend, in that there seems to be a near-linear shape in the front part of the advertising response curve in our study. These results are similar to those seen in the study by Johnson et al (2014) whose findings suggested a linear increase in advertising response up to the maximum frequency level measured which was 50.

There are some possible reasons to explain the higher levels of frequency being the norm for IDA impressions. Research has indicated that in the case of IDA, as compared to other media, the probability of a user being exposed to an advertisement is much lower. This is due to a number of possible reasons. One of the reasons is the fact that IDA advertisements occupy a significantly smaller portion of the screen as compared to other media such as television. This increases the chances of an IDA advertisement of not being viewed by the user (Chatterjee, et al, 2003). Another reason is a consumers' relative lower attention to IDA impressions due to the large volume and variety of content available on the internet that creates a cognitive overload. This leads to higher distraction on a website page where an IDA banner advertisement is typically exposed. As a result consumers tend to notice the internet content and ignore the IDA advertisements in a phenomenon termed as 'banner blindness' (Nielsen, 2007). Other studies such as the one by Dreze and Hussherr (2003) have suggested that consumers tend to notice the IDA advertisements only at pre-attentive levels. Their experiment used a novel eye-tracking technology which showed that only 49.6% of the respondents noticed the IDA banner advertisements they had been exposed to despite the respondents being exposed to the advertisements in a low clutter controlled environment that had been simulated in an experimental setting. Importantly the study highlighted the fact that the probability of users noticing IDA impressions was significantly smaller than noticing television impressions, thereby implying that a higher frequency of impressions was necessary for IDA than for television advertising.

Another reason is linked to the incidence of higher advertising clutter on IDA as compared to traditional media. Advertising clutter is the number of advertisements that appear inside a media vehicle within a defined space or time. In other words it is the “density of advertisements in a media vehicle” (Ha, 1996). Many studies over the years have highlighted the issue of advertising clutter, an issue that seems to transcend all media. This problem adversely impacts the effectiveness of advertising due to additional cognitive load on consumers due to the sheer volume of advertisements (Kent and Allen, 1994), confusion in minds of consumers in case advertisements are from similar categories and irritation due to interruption of the consumer’s experience while consuming content (Ha, 1996). The advertising clutter on the internet is higher than any other media due to its global footprint (Breuer and Brettel, 2012) and the prevalence of numerous formats and excessive number of advertisements on a single web-page (Lee and Cho, 2010). As per one estimate, an average person in the US sees 287 internet advertisements daily (Holler, 2011). There are many more advertisements and in many more formats that a user is exposed to on the internet than on any other media.

Given the aforesaid reasons, it is perhaps not surprising that findings from a field study that tested ad-recall across many traditional media and IDA showed that the conversion from vehicle exposure to advertising exposure was only 11% as compared to 60% for television advertising and 53% for newspaper advertising (Danaher and Dagger, 2013). This suggests that for an IDA advertisement to have a similar advertising exposure as a television advertisement, the IDA frequency levels would have to be at least six times more than that of television advertising. Not surprisingly, researchers have suggested that a higher frequency of exposures is required on IDA than on traditional media in order to ensure a parity in the actual quantum of advertising exposure amongst consumers (Lee and Cho, 2010; Rappaport, 2010).

Further evidence of existence of higher peak frequency for IDA impressions

It is generally accepted that advertising has a far greater impact on attitudinal metrics than on purchase metrics. A recent study by Millward Brown and Dynamic Logic (2012) showed that an increase of IDA impression from one to two caused a higher lift for attitudinal metrics such as advertising awareness than on purchase intent. If this is indeed the case, then for our data-set, the impact of IDA impressions should be greater on attitudinal metrics than on the purchase metric (which is a conversion rate). Moreover, it is likely that the peak conversion rate would be reached at much higher frequency levels. In our data-set, attitudinal metrics can be calculated by using website visits to the advertiser's website as a surrogate measure. Researchers have suggested that website visits is a suitable manifestation of brand attitude metrics (Ilfeld and Winer, 2002).

Therefore, in order to further validate the evidence that higher IDA impression frequency level is necessary, a similar analysis was done using visitation rate as the dependent variable (instead of conversion rate). Visitation rate was defined as number of users who visited divided by the total number of users. The rest of the model remained unchanged. The findings of the analysis clearly suggested that IDA impressions have a greater impact on attitude towards a brand (as manifested by higher visitation rates) than they have on purchases (as manifested by conversion rates). The adjusted R^2 of the model where the dependent variable is a visitation rate is 0.948. Moreover coefficients of almost all the independent, moderator and interaction variables are significant at the 99% confidence level. The results of the model are in Table 5 below:

Table 5: Result of model on visitation rate

Sample: 1 550
Included observations: 550

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.727118	0.091709	7.928538	0.0000
FREQ	0.072889	0.019110	3.814096	0.0002
FREQ^2	-0.010737	0.001557	-6.895869	0.0000
FREQ^3	0.000323	4.04E-05	7.994316	0.0000
INVOLV	-3.479175	0.072495	-47.99218	0.0000
INVOLV*FREQ	0.236668	0.013659	17.32694	0.0000
INVOLV*(FREQ^2)	-0.007020	0.000524	-13.39348	0.0000
FAMILIAR	-1.464540	0.089498	-16.36403	0.0000
FAMILIAR*FREQ	0.067101	0.014144	4.743978	0.0000
FAMILIAR*(FREQ^2)	-0.001640	0.000538	-3.050983	0.0024
CUMTIME	-8.81E-08	1.80E-08	-4.900597	0.0000
MEDTIME	-7.01E-06	1.20E-06	-5.815027	0.0000
INVOLV*CUMTIME	-4.78E-08	1.02E-08	-4.683927	0.0000
FAMILIAR*CUMTIME	1.10E-07	1.79E-08	6.157535	0.0000
INVOLV*MEDTIME	1.13E-07	1.41E-06	0.080359	0.9360
FAMILIAR*MEDTIME	9.99E-06	1.69E-06	5.907143	0.0000
PREM	0.055125	0.061241	0.900144	0.3685
FESTIVE	-0.410274	0.056354	-7.280367	0.0000

R-squared	0.949737	Mean dependent var	-1.107405
Adjusted R-squared	0.948131	S.D. dependent var	1.176212
S.E. of regression	0.267880	Akaike info criterion	0.235621
Sum squared resid	38.17603	Schwarz criterion	0.376673
Log likelihood	-46.79583	Hannan-Quinn criter.	0.290742
F-statistic	591.3154	Durbin-Watson stat	0.643766
Prob(F-statistic)	0.000000		

Furthermore the charts in Appendix D show that the visitation rates in all four contexts – low consumer involvement, high consumer involvement, low brand familiarity and high brand familiarity are significantly higher than the conversion rates for the corresponding contexts. Finally, the frequency at which peak visitation rate occurs is much higher than the frequency at which peak conversion rate occurs, thus providing ample evidence that the peak conversion rate IDA impression frequency levels as evidenced in our study are within a reasonable range.

Existence of inverted 'U-shape' curve for advertising response amongst high involvement consumers rather than a downward sloping curve

Hypothesis H2 suggested that the conversion rate would be a downward sloping curve and not an inverted 'U-shape' curve as seen in the findings of this study. The reason for this could be related to the operationalization of the variable, consumer involvement. Consumers were classified as being highly involved if they had at least one search click in their consumer journey. Instead of a blanket application of this rule, perhaps a more nuanced calibration is necessary. Users can exhibit differences in search behaviour and these differences can highlight differences in levels of involvement. Differences in search behaviour can be in terms of volume, i.e. number of searches performed, as well in terms of type of search performed, i.e. whether a search is for a generic keyword or for a specific brand keyword. Such differences across users can be used to classify users into varying degrees of involvement.

For example, a higher volume of searches by a user can be a gauge for a consumer with a relatively higher degree of involvement than a user who has performed fewer searches. Likewise, if a user performs a generic category search such as 'holiday' may be a manifestation of a consumer who has a relatively lower degree of involvement, than a user who performs a specific brand search such as 'promotions at the specific resort'. Therefore, by operationalizing consumer involvement by incorporating nuances in search behaviour can possibly throw better light on the impact of IDA impression frequency on conversion rate.

Also, whilst hypothesis 2 was not supported, i.e. there was an absence of the downward sloping advertising response curve for consumers with high involvement, the conversion rate peaked at a range of 51-60. This range is lower than the peak conversion range of 61-70 for consumers with low involvement. This difference supports earlier academic papers that indicated that the frequency of advertising exposures required to drive advertising's effectiveness will be lower for consumers with high involvement than for consumers with low involvement (Tellis, 1998).

Moderating Effects

Whilst the coefficients for the two moderators for spacing were not significant in the model, the trend analysis do show some evidence that the time or spacing factor between and across IDA impressions does have an impact on conversion rate based advertising responses. For consumers with low involvement as well those with low brand familiarity the conversion rates are highest at all or most IDA impression frequency levels when the median time between IDA impressions is at moderate levels, i.e. 12-18 hours. The conversion rate is lower at all IDA impression frequency levels that are higher (36-42 hours) or lower (0-6 hours). Similarly, the conversion rates are higher at all or most IDA impression frequency levels when cumulative time across all IDA impressions was at a moderate level of 41-50 days. Conversely, the conversion rate is lower at higher (81-90 days) or lower (1-10 days) cumulative times.

The aforementioned evidence corroborates the findings from earlier studies that advertising exposures should neither be too concentrated, nor too spread out. Braun and Moe (2011) alluded this to the phenomenon of ‘wear-out’ if advertising is repeated too quickly, and an opposing phenomenon of ‘restoration’ when a sufficient gap or space is allowed between advertising exposures. In their analysis they showed that a three week gap between IDA impressions actually restored an advertisement to the same level as a new advertisement. In the analysis of our study the median time between IDA impressions and cumulative time across IDA impressions was significantly higher for users (cookies) who purchased than those who didn’t.

Earlier researchers such as Mahajan and Muller (1986) also showed evidence that regular advertising bursts with sufficient gaps are more effective than a single concentrated advertising burst for products with ‘S-shape’ advertising response curve. As an ‘S-shape’ response curve is likely to be present for products with low familiarity, evidence from our study too supports the higher effectiveness of spacing than concentration in the context of consumers with low brand familiarity.

On the other hand, consumers with high brand familiarity wherein the conversion rate is highest at lower IDA impression frequency level, i.e. 1-10, the increase in median time at this frequency level of IDA impressions reduces the conversion rate. This supports the recommendations by researchers such as Tellis (1988) that higher brand familiarity needs lower frequency of exposures.

IMPLICATIONS FOR ADVERTISERS

Actionable findings

The findings from the study as shown in Table 6 are useful guidelines for marketers in the travel and leisure category. Implementation of these guidelines can help marketers improve the ROI of IDA campaigns by helping to regulate the deployment of IDA impressions in order to drive higher online purchase conversions.

Table 6: Summary of findings

	Peak frequency range of IDA impressions	Cumulative time across first and last IDA impression	Median time between consecutive IDA impressions
Low Involvement	61-70	41-50 days	12-18 hours
High Involvement	51-60	NA[1]	NA[1]
Low Brand Familiarity	71-80	NA[1]	12-18 hours
High Brand Familiarity	1-10	NA[1]	0-6 hours

[1]Figures not shown as the actual findings did not concur with the hypothesized findings.

Improvement in ROI of IDA

By regulating the deployment of IDA impressions as per the guidelines provided above, ROI of campaigns can be improved significantly. As an illustration, a stylized calculation has been done with the existing data-set that has been used for this study.

As a first step, if the IDA impression frequency were to be capped at the peak conversion rate levels, the expected savings in terms of number of IDA impressions will be as shown in table 7 below:

Table 7: Estimated Gain/ (Loss) based on limiting IDA impressions to the peak conversion rate frequency level

	Peak Frequency Range [column A]	Potential number of impressions saved [column B]	Potential loss of conversions [column C]	Gain (Loss) = Cost of impressions[1] saved less conversion revenue[2] [column D]
Low Involvement	61-70	187,532,509	-1,603	US$ 777,363
High Involvement	51-60	7,501, 092	-3,001	(US$ 262,595)
Low Brand Familiarity	71-80	118,572,931	-1,143	(US$ 478,565)
High Brand Familiarity	1-10	144,396,934	-21,492	(US$ 1,427,215)

[1]Cost of impressions estimated at US$ 5 per thousand impressions.
[2]Conversion revenue estimated at US$ 100 per average conversion.

Column B consists of the 'surplus' IDA impressions saved by curtailing IDA impressions at the peak conversion rate frequency level. Column C provides the potential loss of conversions which were driven by the surplus IDA impressions. Assuming a cost per thousand impression of $5 and revenue per conversion of $100, gives us the gains (loss) in column D.

With the exception of the low consumer involvement context, there are more instances of potential losses, than gains if the IDA impressions are not re-deployed. Hence, in order to generate gains, the surplus IDA impressions ought to be re-deployed to reach more users at lower IDA impression frequency levels. Based on the four set of guidelines developed – one each for low involvement, high involvement, low brand familiarity and high brand familiarity, the potential increase in conversion revenue has been calculated in the stylised workings done for each of the four scenarios:

For the low involvement scenario (Table 8), the surplus IDA impressions (which total 187,532,509 impressions) are assumed to be re-deployed across various IDA impression frequency levels, with each level being a frequency range. Thus, 187,532, 509/5 = 37, 506, 502 users can be targeted at the frequency level of 1-10. At the estimated conversion rate (based on the model) of 0.015%, 5485 conversions can be potentially garnered. This amounts to US$ 548,500 in incremental revenue, assuming a revenue of US$ 100 per conversion. However, after accounting for the cost of redeploying 187,532,509 surplus IDA impressions (@ US$ 5 per 1000 impressions), the estimated returns is a negative US$ 389,131. The negative returns are even higher if the surplus IDA impressions were to be re-deployed at the peak conversion rate frequency level of 71-80. Thus, in the low involvement scenario, based on the data-set of the campaigns analysed in this study, the recommendation would be not to re-deploy the surplus IDA impressions and save a potential US$ 777,363 (as shown in Table 7). Interestingly, in the low involvement scenario, the lowest negative return can be garnered at a frequency level of 1-10, and not at the peak conversion rate frequency level of 71-80. This is because the rate of increase in conversions is lower than the rate of increase in costs from one frequency range to the next.

Table 8: Scenario wherein surplus IDA impressions are re-deployed at lower frequency levels in case of consumers with low involvement

Low Involvement					
Total Impressions saved (a) =		187,532,509			
Frequency range	Assumed average frequency per consumer (b)	Estimated conversion rate (c)	Number of consumers targeted (d) = (a)/(b)	Estimated conversions (e) = (c) x (d)	Estimated returns (US$) [1]
1-10	5	0.015%	37,506,502	5,485	(389,131)
11-20	15	0.024%	12,502,167	2,981	(639,516)
21-30	25	0.035%	7,501,300	2,635	(674,194)
31-40	35	0.047%	5,358,072	2,518	(685,883)
41-50	45	0.057%	4,167,389	2,394	(698,310)
51-60	55	0.064%	3,409,682	2,199	(717,740)
61-70	65	0.067%	2,885,116	1,931	(744,560)
71-80	75	0.065%	2,885,116	1,862	(751,445)

Peak returns occur at frequency range of 1-10.

Returns at peak conversion rate.

[1] Estimated returns = Estimated conversions (e) x US$ 100 per conversion, less cost of impressions i.e. 187,532,509 impressions at $US 5 per 1000 impression.

In the high involvement scenario (Table 9), the highest incremental revenue is garnered by re-deploying saved impressions at the frequency level of 31-40 and not the peak conversion rate frequency level of 51-60.

Table 9: Scenario wherein surplus IDA impressions are re-deployed at lower frequency levels in case of consumers with high involvement

High Involvement					
Total Impressions saved (a) =		7,501,092			
Frequency range	Assumed average frequency per consumer (b)	Estimated conversion rate (c)	Number of consumers targeted (d) = (a)/(b)	Estimated conversions (e) = (c) x (d)	Estimated returns (US$) [1]
1-10	5	2.120%	1,500,218	31,797	3,142,236
11-20	15	5.149%	500,073	25,749	2,537,384
21-30	25	9.814%	300,044	29,446	2,907,074
31-40	35	14.980%	214,317	32,104	3,172,892
41-50	45	18.691%	166,691	31,157	3,078,175
51-60	55	19.462%	136,383	26,542	2,616,738
61-70	65	17.260%	115,401	19,918	1,954,326
71-80	75	13.309%	115,401	15,359	1,498,399

Peak returns occur at frequency range of 31-40.

Returns at peak conversion rate.

[1] Estimated returns = Estimated conversions (e) x US$ 100 per conversion, less cost of impressions i.e. 187,532,509 impressions at $US 5 per 1000 impression.

In the case of low brand familiarity (Table 10) and high brand familiarity (Table 11), the highest incremental revenue can be garnered by re-deploying the saved IDA impressions at the peak conversion rate frequency level.

Table 10: Scenario wherein surplus IDA impressions are re-deployed at lower frequency levels in case of consumers with low brand familiarity

Low Brand Familiarity					
Total Impressions saved (a) =	118,572,931				
Frequency range	Assumed average frequency per consumer (b)	Estimated conversion rate (c)	Number of consumers targeted (d) = (a)/(b)	Estimated conversions (e) = (c) x (d)	Estimated returns (US$) [1]
1-10	5	0.009%	23,714,586	2,179	(375,001)
11-20	15	0.038%	7,904,862	3,014	(291,464)
21-30	25	0.118%	4,742,917	5,603	(32,589)
31-40	35	0.279%	3,387,798	9,466	353,783
41-50	45	0.516%	2,634,954	13,600	767,156
51-60	55	0.761%	2,155,871	16,416	1,048,718
61-70	65	0.918%	1,824,199	16,739	1,081,020
71-80	75	0.924%	1,824,199	16,852	1,092,384

Peak returns occur at peak conversion rate frequency 71-80.

[1] Estimated returns = Estimated conversions (e) x US$ 100 per conversion, less cost of impressions i.e. 187,532,509 impressions at $US 5 per 1000 impression.

Table 11: Scenario wherein surplus IDA impressions are re-deployed at lower frequency levels in case of consumers with high brand familiarity

High Brand Familiarity					
Total Impressions saved (a) =	144,396,934				
Frequency range	Assumed average frequency per consumer (b)	Estimated conversion rate (c)	Number of consumers targeted (d) = (a)/(b)	Estimated conversions (e) = (c) x (d)	Estimated returns (US$)[1]
1-10	5	0.395%	4,125,000	16,311	1,527,929
11-20	15	0.354%	4,125,000	14,619	1,152,514
21-30	25	0.315%	4,125,000	12,988	783,167
31-40	35	0.277%	4,125,000	11,442	422,323
41-50	45	0.242%	3,208,821	7,778	55,832
51-60	55	0.210%	2,625,399	5,519	(170,121)
61-70	65	0.181%	2,221,491	4,020	(320,015)
71-80	75	0.155%	2,221,491	3,436	(378,371)

Peak returns occur at peak conversion frequency of 1-10.

[1] Estimated returns = Estimated conversions (e) x US$ 100 per conversion, less cost of impressions i.e. 187,532,509 impressions at $US 5 per 1000 impression.

In three out of the four scenarios, significant increases in nett return on investment (ROI) can be potentially generated. In the high involvement scenario, the potential nett increase in ROI by re-deploying surplus IDA impressions is the highest at US$ 2,910,297. In the low brand familiarity scenario, the nett increase in ROI by such a re-deployment is US$ 613,819. Finally, in the high brand familiarity scenario, the potential nett increase in ROI is US$ 100,714. For the low involvement scenario, the nett increase in ROI is the highest if the surplus IDA impressions were to be saved and not re-deployed. The summary Table 12 below shows the potential increase in nett ROI in each of the four scenarios:

Table 12: Summary table of potential increase in ROI by re-deployment of IDA impressions based on optimal conversion revenue criteria

	Estimated savings (Loss) from removal of excess frequencies[1]	Gains from re-deployment at optimal frequency[2]	Nett increase in ROI from re-deployment at optimal frequency
Low Involvement[1]	US$ 777,363	No gains, hence didn't re-deploy	**US$ 777,363**
High Involvement[1]	(US$ 262,595)	US$ 3,172,892	**US$ 2,910,297**
Low Brand Familiarity	(US$ 478,565)	US$ 1,092,384	**US$ 613,819**
High Brand Familiarity	(US$ 1,427,215)	US$ 1,527,929	**US$ 100,714**

[1] Cost of thousand impressions = US$ 5. [2] Assume average conversion value = US$ 100.

These stylised workings can help marketers determine the most optimal level of IDA impression frequency required for IDA campaigns. The frequency guidelines outlined can serve as a useful starting point and thereafter various 'what if' scenarios can be simulated in order to choose the most appropriate IDA impression frequency level. The advertising budget for the campaigns analysed in this study were approximately US$ 5 million. A US$ 100,000 increase in conversion revenue has the potential to increase the ROI by 2% whereas a US$ 2.9 million increase in conversion revenue has a potential to increase the ROI by 40%. Clearly, the potential improvement in ROI for IDA campaigns is significant.

LIMITATIONS OF THE STUDY

The study, whilst being useful and relevant given the importance of IDA in the world of internet advertising, has some limitations that are outlined as follows:

Assumption that IDA impression = IDA exposure

One of the primary assumptions made is that an impression of an IDA is assumed to be equivalent to an exposure. This is consistent with the assumptions made by prior researches in traditional media that evaluated the individual sales impact of a vehicle exposure (Deighton et al, 1994; McDonald, 1995; Jones, 1995a; 1995b). Similar assumptions have been made in IDA based studies as well (Chatterjee et al, 2003; Manchanda et al, 2006; Braun and Moe, 2011; Nottorf, 2013). Researchers have acknowledged the challenge of measuring the impact of actual advertising exposures as against vehicle exposures in field studies, irrespective of whether the field studies are measuring the impact of advertising on traditional media or internet (Danaher and Dagger, 2013).

Assumption that a unique cookie = unique user

An assumption is also made wherein a unique cookie is assumed to be a unique user. This is consistent with a similar assumption made by other IDA studies such as the one by Manchanda et al (2006). To the best of our knowledge, the assumption that a unique cookie is a unique consumer, is still the most commonly used approach when identifying unique consumers on the internet. Moreover, the cookie deletion check on done on the data-set used for this purposes of this study, indicates that the problem of multiple identities is somewhat lower than expected.

Non-inclusion of competitive effects

Studies have shown that repetition of advertising exposures works even in highly competitive markets and has a significant impact on metrics such as brand awareness, brand shares, brand preference and brand choice (D'Souza and Rao, 1995). In another study, the presence of competitive clutter did not adversely impact advertising recall, attitudes towards advertising or trial intent (Lee and Cho, 2010). However, other studies have suggested that competitive clutter does reduce the effectiveness of advertising. Danaher, Bonfrer and Dhar (2008) showed that advertising elasticity is lower whenever there is higher competitive clutter in advertising. Therefore, given the high level of advertising clutter on the internet especially in the category analyzed in this study, any result that shows evidence of the impact of advertising exposure frequency is by extension a conservative result.

Possible cross-channel effects not accounted

An analysis using real-world data from a European office furniture supplier, showed that the share of cross-channel effects from offline channels (faxes) to online channels was just 6% compared to the 94% share of effects from offline channels to offline results (Wiesel et al, 2010). In contrast the share of effect of online channels (paid search advertising) to offline results was 73%. Another recent research has shown that IDA had little or no effect in driving offline purchases suggesting that IDA may have a much larger impact on online purchases should the website towards which the advertising is targeted to, have the provision for e-commerce (Danaher and Dagger, 2013). Therefore the lack of measurement of offline effects makes our results even more conservative than the probable real effects.

FUTURE RESEARCH

The current study opens up possibilities of other researches in a number of areas related to the task of understanding the role of IDA in driving marketing goals:

1. This study has shown evidence that IDA impression frequency does indeed drive both conversions and website visits. In a future research, visits can be used as a co-variate to determine the impact of IDA impression frequency on purchase conversions. Moreover, visits can be calibrated based on volume, time-spent per visit and type of pages visited and a brand equity measure could be developed. Given that marketers constantly need evidence to show the impact of advertising on marketing goals, the prospect of using a brand equity measure along with the other advertising variables, is an interesting area to explore.

2. As highlighted in this study, operationalization of consumer involvement using search can be improved significantly by including other factors such as volume and type of search. This would need more granular deployment of tracking codes at the keyword level. Though this process is more time consuming and would also incur extra tracking charges, the potential benefits are likely to outweigh the likely cost increase.

3. This study has analyzed the IDA impression frequency's impact at a campaign level. As data can be collected at a copy and publisher level, future studies can

be undertaken to develop optimal frequency guidelines at a copy and publisher level as well. The resultant learnings would be extremely relevant for advertisers in order to improve the ROI of IDA even further.

4. Cross device internet usage is becoming increasingly widespread amongst consumers. As a result advertising too is moving toward device neutrality. As the share of mobile advertising becomes larger, determining the optimal level of IDA impression frequency across devices will be a critical area of research. Currently cookie based tracking does not allow for identification of the same user across devices. Solutions are being developed to track consumers across multiple devices and platforms. Once such data is made available, the natural progression of this study would entail including mobile IDA impressions in order to refine the level of IDA impression frequency that is most optimal.

CONCLUSION

The internet display advertising (IDA) is a $56.5 billion (ZenithOptimedia, 2014) industry and is expected to witness a double digit for the foreseeable future. This has led advertisers to ask tough questions from their advertising agencies on how effective is their internet advertising strategy. The findings of this research will go a long way in improving the understanding of how IDA works, as well as provide some definitive guidelines to optimize IDA impression frequency levels. By implementing the proposed guidelines, advertisers in the travel and leisure category stand to benefit significantly from potentially higher ROI from IDA. Moreover, a similar approach can be undertaken on data-sets from campaigns for other product categories in order to make these guidelines more scalable and practically implementable across more product categories.

This research also provides some interesting avenues for future researches to improve the efficacy of IDA even further. Moreover, the handy software codes developed to extract, prepare and manage the big data-sets from ad-server log files, will be a big boost to future researches in this field. As advertisers invest larger share of their advertising dollars on IDA, more questions regarding its effectiveness will continue to be raised. Therefore, it is the expectation of the researcher that this type of study will be the first of many more.

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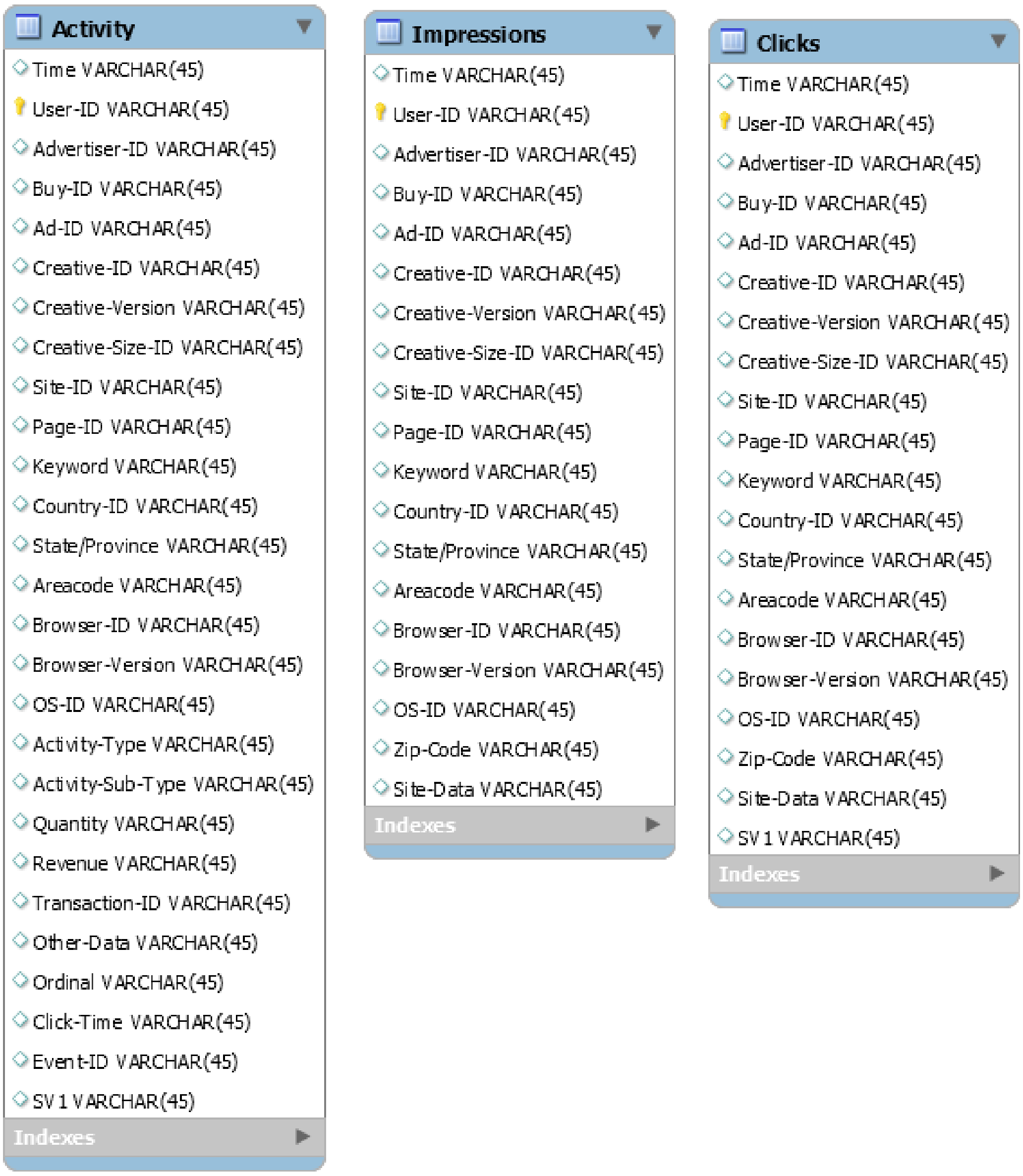
APPENDIX A

Raw data-set entity diagram



APPENDIX A

Raw data-set file structures

Structure of Clicks Files

```
> clk_dir = list.files("C:/Users/RQuek01/Desktop/AugSept/Clicks/LAST
TWO WEEKS",full.name=TRUE,recursive=TRUE)
> clk_data = read.table(clk_dir[1],header=TRUE,sep="þ",fill=TRUE);
str(clk_data)
'data.frame':   26084 obs. of  20 variables:
 $ Time           : Factor w/ 21384 levels "09-16-2014-00:09:02",..: 80 240 256
350 39 237 215 ...
 $ User.ID        : num  2.48e+18 2.50e+18 2.45e+18 2.49e+18 2.45e+18 ...
 $ Advertiser.ID  : int  3918882 3918882 3918882 3918882 3918882 3918882
3918882 3918882 ...
 $ Buy.ID         : int  8246682 8246682 7351801 7351801 8234137 8227450
8227450 8246682 ...
 $ Ad.ID          : int  284075439 284079736 267986286 267986286
283907662 283785683 283783790 ...
 $ Creative.ID    : int  59123438 59123607 0 0 59008534 58929069 58929069
59123628 58929459 ...
 $ Creative.Version: int  1 1 0 0 1 1 1 1 1 2 ...
 $ Creative.Size.ID: Factor w/ 7 levels "0x0","160x600",..: 3 3 7 7 2 3 3 3 6 3
...
 $ Site.ID        : int  1568374 693142 1379239 1379239 1563866 1568374
1568374 1568374 ...
 $ Page.ID        : int  111125033 111124653 93864055 93864055 110811495
110628102 110624317 ...
 $ Keyword        : logi  NA NA NA NA NA NA ...
 $ Country.ID     : int  176 176 199 199 176 134 134 176 134 199 ...
 $ State.Province  : Factor w/ 22 levels "","AB","CA","CO",..: 1 1 1 1 1 1 1 1
1 1 ...
 $ Areacode       : int  0 0 0 0 0 0 0 0 0 0 ...
 $ Browser.ID     : int  30 26 26 28 28 5 28 30 26 27 ...
 $ Browser.Version : num  0 32 31 0 0 8 0 0 32 0 ...
 $ OS.ID          : int  501012 22 22 501013 501026 22 501013 501012 2 7 ...
 $ Zip.Code       : Factor w/ 61 levels "","10009","10021",..: 1 1 1 1 1 1 1 1 1
1 ...
 $ Site.Data      : logi  NA NA NA NA NA NA ...
 $ SV1            : int  0 0 0 0 0 0 0 0 0 0 ...
```

Structure of Impressions Files

```
> imp_dir =
list.files("C:/Users/RQuek01/Desktop/AugSept/Impressions/LAST TWO
WEEKS",full.name=TRUE,recursive=TRUE)
> imp_data = read.table(imp_dir[1],header=TRUE,sep="þ",fill=TRUE);
str(imp_data)
'data.frame':   20733721 obs. of  19 variables:
 $ Time            : Factor w/ 86711 levels "09-16-2014-00:04:18",..: 1591 2735
2095 659 574 574 ...
 $ User.ID         : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Advertiser.ID   : int  3918882 3918882 3918882 3918882 3918882 3918882
3918882 3918882 ...
 $ Buy.ID          : int  8245535 8228907 8204269 8228907 8246323 8246323
8246323 8246682 ...
 $ Ad.ID           : int  284056697 283800679 284393258 283800679
284157102 284157102 284157102 ...
 $ Creative.ID     : int  59098323 58939718 59279389 58939718 59172994
59172994 59172994 59123628 ...
 $ Creative.Version: int  1 1 2 1 1 1 1 1 1 1 ...
 $ Creative.Size.ID: Factor w/ 10 levels "0x0","1024x66",..: 9 6 6 6 6 6 6 6 6 3
...
 $ Site.ID         : int  1061597 1061601 872317 1061601 1702798 1702798
1702798 1568374 ...
 $ Page.ID         : int  111077676 110629412 111397737 110629412
111166942 111166942  ...
 $ Keyword         : logi  NA NA NA NA NA NA ...
 $ Country.ID      : int  134 134 199 134 176 176 176 176 176 107 ...
 $ State.Province  : Factor w/ 64 levels "","AB","AK","AL",..: 1 1 1 1 1 1 1 1
1 1 ...
 $ Areacode        : int  0 0 0 0 0 0 0 0 0 0 ...
 $ Browser.ID      : int  28 5 26 5 30 30 31 31 5 26 ...
 $ Browser.Version : num  0 11 32 10 0 0 0 0 11 31 ...
 $ OS.ID           : int  22 22 22 501026 501012 501012 501012 501012 22 22
...
 $ Zip.Code        : Factor w/ 3450 levels "","01002","01020",..: 1 1 1 1 1 1 1 1
1 1 ...
 $ Site.Data       : logi  NA NA NA NA NA NA ...
```

Structure of Activities File

```
> act_dir = list.files("C:/Users/RQuek01/Desktop/AugSept/Activities/LAST
TWO WEEKS",full.name=TRUE,recursive=TRUE)
> act_data = read.table(act_dir[1],header=TRUE,sep="þ",fill=TRUE);
str(act_data)
'data.frame':   147372 obs. of  28 variables:
 $ Time            : Factor w/ 55949 levels "09-16-2014-00:00:00",..: 33761
33707 33699 33677 ...
 $ User.ID         : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Advertiser.ID   : int  NA NA NA NA NA NA NA NA NA NA ...
 $ Buy.ID          : int  NA NA NA NA NA NA NA NA NA NA ...
 $ Ad.ID           : int  NA NA NA NA NA NA NA NA NA NA ...
 $ Creative.ID     : int  NA NA NA NA NA NA NA NA NA NA ...
 $ Creative.Version : int  NA NA NA NA NA NA NA NA NA NA ...
 $ Creative.Size.ID : Factor w/ 8 levels "","0x0","160x600",..: 1 1 1 1 1 1 1 1 1
1 ...
 $ Site.ID         : int  NA NA NA NA NA NA NA NA NA NA ...
 $ Page.ID         : int  NA NA NA NA NA NA NA NA NA NA ...
 $ Keyword         : logi  NA NA NA NA NA NA ...
 $ Country.ID      : int  199 199 199 199 199 199 114 114 199 199 ...
 $ State.Province   : Factor w/ 48 levels "","AB","AL","AZ",..: 1 1 1 1 1 1 1 1
1 1 ...
 $ Areacode        : int  0 0 0 0 0 0 0 0 0 0 ...
 $ Browser.ID      : int  30 30 30 30 30 30 31 31 30 30 ...
 $ Browser.Ver     : num  0 0 0 0 0 0 0 0 0 0 ...
 $ OS.ID           : int  501012 501012 501012 501012 501012 501012 501012
501012 501012 501012 ...
 $ Local.User.ID   : logi  NA NA NA NA NA NA ...
 $ Activity.Type   : Factor w/ 18 levels "attra504","cnrws001",..: 1 1 1 1 1 1 1
1 1 1 ...
 $ Activity.Sub.Type: Factor w/ 47 levels "cnpro519","cnrws903",..: 26 26 25
26 26 26 26 26 25 26 ...
 $ Quantity        : int  1 1 1 1 1 1 1 1 1 1 ...
 $ Revenue         : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Transaction.ID  : logi  NA NA NA NA NA NA ...
 $ Other.Data      : Factor w/ 5904 levels
"","~oref=http://10.136.136.50/Homepage/Promotions",..: 742 742 1481 742
742 1481 742 742 1457 742 ...
 $ Ordinal         : Factor w/ 146688 levels "","1","1000050437683",..: 1359
12465 88356 54514 ...
 $ Click.Time      : Factor w/ 19538 levels "","08-17-2014-00:15:44",..: 1 1 1
1 1 1 1 1 1 1 ...
 $ Event.ID        : int  0 0 0 0 0 0 0 0 0 0 ...
 $ SV1             : int  NA NA NA NA NA NA NA NA NA NA ...
```

Description of fields in the data set

This data is used to construct models that will quantify the impact of digital advertisements on RWS's ecommerce conversions between and.

- Impressions:
- Clicks:
- Activities:
- Paths:
    - Ecommerce Conversions:
        - Conversions with no previous interactions:
        - Conversions with 1 previous interaction:
        - Conversions with >1 previous interactions:

Data elements:

- **Time**[aci]
  Displays the local event time in MM-DD-YYYY-24HH:MI:SS format.

- **User-ID**[aci]
  The DoubleClick cookie ID. A zero (0) is provided if the browser does not accept cookies or the user has opted-out.

- **Advertiser-ID**[aci]
  Unique ID of the advertiser.

- **Buy-ID**[aci]
  Unique ID of the campaign.

- **Ad-ID**[aci]
  Unique ID of the ad placement.

- **Creative-ID**[aci]
  Unique ID for the creative (banner).

- **Creative-Size-ID**[aci]
  Creative size dimension in pixels (WxH).

- **Site-ID**[aci]
  Unique ID for the site where the ad ran.

- **Page-ID**[aci]
  Unique ID for the site page/ placement where the ad ran.

- **Keyword**[aci]
  The targeted keyword to which the ad served. Keywords appear in ad tags as ;kw=<keyword>. This is not the DART Search keyword term. **Currently this field is blank. Hence not used.**

- **Country-ID**[aci]
  ID of the country where the user resides. This is derived from the IP address.

- **State/Province**[aci]
  ID for user's state or province (US/Canada) based on IP address. **Currently this field is blank as the data is not from US/Canada. Hence not used.**

- **Browser-ID**[aci]
  ID of the browser type.

- **Browser-Ver**[aci]
  Browser version.

- **OS-ID**[aci]
  ID of the operating system.

- **Activity-Type**[a]
  Identifies the activity of the user. Some possibilities are leads, sales, etc. As passed using the "type=" key-value.

- **Activity-Sub-Type**[a]
  Identifies the category under each activity to further break down the activity type. As passed using the "cat=" key-value. For example, sales can appear within SISTIC and the advertiser's e-commerce site.

- **Quantity**[a]
  Can contain additional values for type or category, for example, sales quantity. As passed using the "qty=" key-value. **Currently only '1's appear. Hence not used.**

- **Revenue**[a]
  Can contain additional values for type or category, for example, sales amount. As passed using the "cost=" key-value.

- **Transaction-ID**[a]
  The advertiser's transaction ID, if relevant for a given activity type. Should only be activated if client is using the "tran=" key-value pair in their Spotlight tags (generally used for storing the client's Order-ID).

- **Other-Data**[a]
  Stores key-value data from the activity string which is not otherwise labeled. (Any key-value that is NOT "src=", "type=", "cat=", "ord=", "u=", "cost=", "qty=", "tran=", "a=", or "b="). **Currently appears as blanks. Hence not used.**

- **Ordinal**[a]
  The advertiser's ordinal ID, if relevant for a given activity type. Passed in the "ord=" key-value (also used for storing the client's Order-ID in sales tags). **Currently appears as blanks. Hence not used.**

- **Click-Time**[a]
  The activity's associated (aka "matched") click or impression time in MM-DD-YYYY-24HH:MI:SS format. **Currently not used.**

- **Event-ID**[a]
  Indicates whether an activity has been matched as a post-click (value of 1) or post-impression (value of 2), or unmatched (value of 0).

- **SV1**[ac]
  DoubleClick Search keyword id. **Currently appears as blanks. Hence not used.**

- **Site-Data**[ci]
  Site's user-supplied info. Data is passed using the "u=" key value. No relation to Local-User-ID. **Currently appears as blanks. Hence not used.**

APPENDIX C

Format of tabulated

Data-set

	Campaign A																										
	Low Brand Familiarity																					High Brand Familiarity					
	Low Involvement																		High Involvement			Low Involvement			High Involvement		
	Total Consumers						Converted Consumers						Non converted consumers														
Frequency of IDA impressions	Count of consumers (cookies)	Total Impressions	Premium Impressions	Mass Impressions	Cumulative Time across impresssions	Median Time between impressions	Total Impressions	Count of consumers (cookies)	Premium Impressions	Mass Impressions	Cumulative Time across impresssions	Median Time between impressions	Total Impressions	Count of consumers (cookies)	Premium Impressions	Mass Impressions	Cumulative Time across impresssions	Median Time between impressions									
1																											
2																											
3																											
4																											
:																											
:																											
:																											
:																											
25,000+																											

APPENDIX D

Results from model using visitation rate as dependent variable