Blocked! The psychology behind the usage of ad-blocking software

Jahan Rafian

Abstract

The use of internet ad-blocking software as a form of online ad avoidance is increasing rapidly, and websites/online advertisers are seeing their revenues decline as a result. Ad-blocking software is free to download, easy to use, and available across a variety of platforms. Approximately 10% of internet users are now blocking ads, and year-over-year growth is close to 40%. Websites and online advertisers have pushed users to whitelist—the term used when users disable their ad-block for a specific site—but have had limited success. This paper evaluates how ad characteristics, demographics, and exposure affect internet ad-blocking usage. Through a survey and statistical analysis, it was determined that demographics and exposure are significant drivers: younger internet users are more likely to use ad-blocking software, and a major inhibitor of ad-blocking growth appears to be lack of mainstream exposure. However, ad characteristics do not have an effect on ad-blocking usage or whitelisting likelihood. The results suggest that ad-blocking software is poised for long-term growth, and websites/online advertisers will need to adapt.

Key words: Advertising, ad-blocking, ad avoidance, internet

Submitted under the faculty supervision of Professor Linli Xu, in partial fulfillment of the requirements for the Bachelor of Science in Business, *summa cum laude*, Carlson School of Management, University of Minnesota, Spring 2015.

1. Introduction

Consumers looking to avoid online ads have the option of using ad-blocking software, which eliminates all exposure to online ads. Ad-blocking used to be a niche pursuit, but new, simple to install ad-blocking software has set the foundation for explosive growth. The number of ad-block users is now growing at roughly 43% a year with over 150,000 ad-blocking app downloads a day (Beck, 2013). Currently, this translates to ~10% of online consumers using ad-blocking software, and 9.26% of all advertising impressions being blocked (Yablonka, 2014). Although global online advertising is growing at over 5% a year (Barnard, 2013), the growing ad-blocking trend represents a revenue threat to online advertisers and websites. Ad-blocking cost Google an estimated $900 million in 2012 (Beck, 2013), and websites are facing declining ad revenue (Rauline, 2014). For some websites with a tech-savvy consumer base, nearly half their daily visitors run ad-blocking software (Gonzalez, 2013).

Previous research on ad avoidance has focused on the effects of ad characteristics and demographics. However, research has primarily focused on other mediums, such as television and print media. In addition, ad-blocking is a more complicated method of ad avoidance than switching a TV channel or lowering the radio volume, and removes any advertising mere exposure effect that users could receive from other, less aggressive ad avoidance tactics. The lack of available data on the drivers of ad-blocking usage led to the question: *How do ad characteristics, demographics, and exposure affect ad-blocking usage?*

This paper attempts to answer this question through primary data gathered via an Amazon Mechanical Turk survey in January 2015. User survey responses measured ad characteristics, demographics, and user exposure against ad-blocking and whitelisting[1] usage.

[1] See Section 2 for explanation of whitelisting

Survey questions used a Likert scale for measurement, and 70 responses were collected in total. All respondents were Amazon MTurk Masters, a designation given by Amazon to MTurk users who have a long history of accurate and high-effort responses.

The results included several key findings. Users who had not previously used ad-blocking software were significantly more interested in using it after a brief explanation of the software, indicating that exposure could drive future ad-blocking use. Demographically, younger internet users are more likely to use ad-blocking software, which may reflect their familiarity with the medium, their weaker heuristics which makes it more difficult to mentally filter out ads, and tendency of being heavier internet users. Gender is not an indicator of ad-blocking usage, and the selected ad characteristics (annoyance, irrelevance, and privacy-invasiveness) are not significant drivers of ad-blocking or whitelisting.

There were some limitations inherent in the methodology. Recreating a realistic advertising experience was difficult; describing an advertisement that disrupts a website from loading may not have the same effect on a user as an actual disruptive advertisement. In addition, users who already use ad-blocking software rarely see internet advertisements, which could alter their perception of ad characteristics and cause them to perceive every ad as highly intrusive. The results are also based on internet users that do not represent the internet user population as a whole. The average user of the survey was young, male, and tech-savvy, which potentially limits the transferability of this paper's results. Finally, the results were self-reported and the sample size was relatively small.

Despite these limitations, better understanding the drivers of ad-blocking usage will be of interest to online advertisers, website administrators, and ad-block developers. In particular, small websites that are being adversely affected by ad-blocking and want to adjust their advertising/whitelisting techniques will find the results interesting. This paper will also fill in the existing research gap on internet ad-blocking, and outline the potential for future ad-blocking growth.

The following section provides an overview of internet ad-blocking technology and history, along with an explanation of whitelisting. Section 3 will review previous research on ad avoidance, and highlight the research gap this paper fills. Section 4 lays out the data collection and statistical analysis methodology, along with the hypotheses. Section 5 shows the statistical results of my hypotheses. Section 6 discusses the implications of the results and other interesting trends found in the data, while Section 7 explores future topics for related research and highlights the key takeaways.

2. Background on Ad-blocking Technology and Whitelisting

Browser-based internet ad-blocking software blocks nearly all online ads, including banner ads, pop-ups, and video ads. Examples of blocked ads include Google sponsored results, Youtube pre-video ads, and Facebook promoted posts. Figure 1 shows what a standard website page looks like pre (Panel A) and post (Panel B) ad-blocking software.

Figure 1: Example of ad-blocking software

Panel A *Panel B*

Ad-blocking software is a “hard” ad avoidance technique. It fully blocks advertisements, which removes any low attention processing by the consumer. Low attention processing refers to the mere exposure effect when a consumer may feel they are fully ignoring an ad, but actually retaining some ad information (Bornstein, R. F., & D'Agostino, P. R, 1994; Ruggieri, S., & Boca, S, 2013). Research shows users often underestimate the effect that this low attention exposure can have on their purchasing behavior (Heath, 2005). Ad-blocking software removes both high attention processing (when a consumer focuses on an ad) and low attention processing, thus making is a hard avoidance technique. A soft avoidance technique only removes high attention processing.

Popular ad-blocking solutions are free to download. The developers make money through user donations, although developers could feasibly seek other revenue generation angles in the future. Ad-blocking solutions are also small (most take less than 30 seconds to download with >1MB internet speed), convenient (available through Chrome and Firefox extension stores), and very user-friendly.

Before the mid 2000’s, internet ad-blocking was possible but difficult. Common methods of ad-blocking included editing host files or changing the Domain Name System (DNS), which can be edited to refuse entry to internet domains associated with advertising cache. Both of these methods require advanced user knowledge and a relatively large time investment. In 2006, the first well-known browser ad-blocking software (Adblock Plus) was made available for download. Since then, a variety of ad-blocking software solutions have become popular for all commonly used browsers, including Microsoft Internet Explorer, Mozilla Firefox, Google Chrome, and Apple Safari. Ad-blocking developers have also released ad-blocking apps for mobile platforms, beginning in 2010. However, because Apple and Google have tighter control over their app marketplaces and greater market share, ad-blocking apps have been banned from both the Apple Appstore and the Android Play Store for the last few years. Although mobile users can still block ads through more complicated techniques, the move has helped Apple and Google retain advertising revenue on mobile platforms.

Because banning ad-blocking software on non-mobile platforms is difficult from a technical and business perspective, advertisers have developed alternative techniques to discourage ad-block usage. Most of these techniques fall under the umbrella of "whitelisting." Whitelisting is simply the term used when users disable their ad-block for a specific site. Whitelisting is a built-in feature in all popular ad-blocking software. For instance, if an internet user frequently browses the Minneapolis Star-Tribune website and enjoys the content, they might whitelist the Star-Tribune website. This means that they will see ads on the Star-Tribune website and Star-Tribune will make advertising revenue from their visits, but ads will still be blocked on other non-whitelisted websites. Websites are naturally very interested in getting their users to whitelist, as it currently offers the best chance of retaining the advertising revenue of ad-block users.

3. Literature Review

Peer-reviewed literature on internet ad-blocking specifically is developing, but there is a substantial amount of research on ad avoidance across various mediums. This research has found a few key explanatory drivers for ad avoidance, including advertisement characteristics and demographics. This literature review is divided into two subsections. First, general advertising theory and research will be discussed. This section will look at how advertising medium and demographics affect ad avoidance. The second subsection looks at specific ad characteristics that influence ad avoidance. This section will first narrow down the multitude of potential ad characteristics to the most relevant characteristics for this paper, and then review the literature which has looked at the selected characteristics.

3.1 Advertising Theory

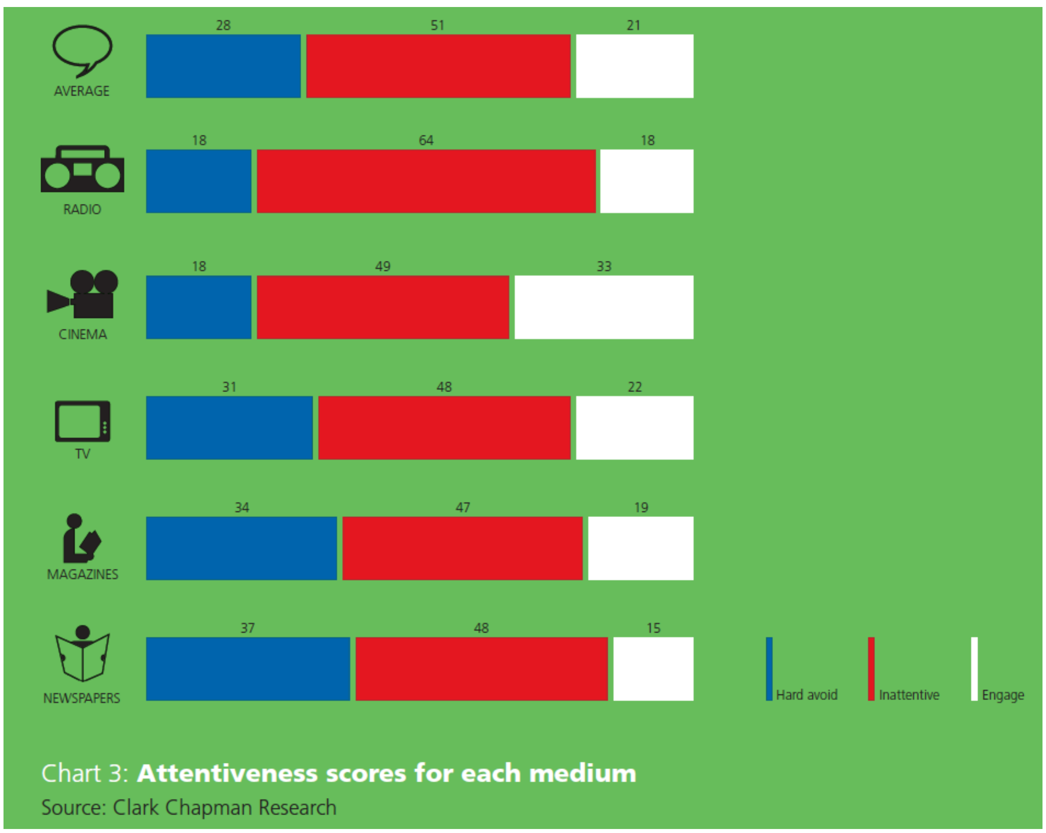
Advertising Medium

Advertising avoidance varies widely based on the medium. Ad avoidance for print ads is straightforward—consumers can simply flip past them (Dahlén, M., & Edenius, M, 2007). Prior research differentiates between hard avoidance in print, which avoids any exposure effect and is achieved by consumers who flip past advertisements instinctively, and soft avoidance, in which consumers glance at the advertisements before flipping the page, leaving consumers vulnerable to the mere exposure effect (Heath, 2005). Figure 2 at the end of this section has more detail on hard vs. soft avoidance rates for various mediums. It is more difficult for consumers to "hard" avoid print ads when they are placed in the middle of an article or feature a jarring color scheme, as consumers focus on the advertisement longer and recall more details after a period of time (Simola, J., Kivikangas, M., Kuisma, J., & Krause, C. M, 2013). Some consumers do enjoy seeing print ads, particularly ads for expensive products (Rosengren, S., & Dahlén, M. (2013), but overall ad avoidance for print media is relatively high, with about a 35% hard avoidance rate for all print media (Heath, 2005).

Consumers who are looking to avoid television ads have traditionally either ignored the television during commercials (behavioral & high attention avoidance) or by switched the channel (mechanical & both high and low attention avoidance) (Rojas-Mendez, J., Davies, G., & Madran, C, 2008). Research indicates that the determinants of switching the channel to avoid an ad (also known as *zapping)* is dependent on a number of factors, including length, amount of previous exposure, and even the time of day (Siddarth, S., & Chattopadhyay, A, 1998). Consumers who zap normally completely avoid the first few advertisements in an advertising pod, but avoidance rates are lower for the later ads in the pod because consumers don't want to miss the any of their chosen program (Tse and Lee, 2001). Both ad avoidance measures are also influenced by ad characteristics, including relevance and uniqueness (Olney, T. J., Holbrook, M. B., & Batra, R. 1991; Dix, S., & Phau, I, 2010). In recent years, new technologies that allow consumers to fast-forward through advertisements have been developed. These new technologies fall under the mechanical avoidance side of avoidance, but their usage is still tempered by engaging ad characteristics such as humor and sexual content. (Yoonjae, N., Kyonghee H., K., & Sungjoon, L. 2010). Usage is also tempered because ads increase viewing enjoyment through diversion for a subset of viewers (Nelson et al, 2009). However, the overall ad avoidance rate in television has dropped from ~90% in the 1980s to ~60%, although sources vary (Teixeira, 2014). Hard avoidance rates are lower at about ~30% (Heath, 2005).

Internet advertising has evolved from simple banner and pop-up advertisements to interactive videos and carefully engineering word-of-mouth campaigns spread through social media. In the process, revenues have increased substantially over the last decade (Barnard, 2013), Internet advertising has also been successful at reaching demographics that are considered difficult to reach through other mediums, such as tech-savvy professionals and college students (Batterham, P. J. 2014). Online ad avoidance was initially similar to print ad avoidance. Users learned to ignore the static banner ads that most websites contained, although most users still noticed the static banner ads contrary to what they might claim (Hervet, G., Guérard, K., Tremblay, S., & Chtourou, M. S, 2011). This is the same concept of low attention vs. high attention that was discussed earlier. The online ad avoidance landscape began to shift when automated ad avoidance methods became available. Current hard internet ad avoidance rates are substantially lower than other mediums at around 10% (Beck, 2013). The current growth of ad-blocking may not be indicative of higher hard internet ad avoidance rates in the future compared to hard internet ad avoidance rates in other mediums, as hard avoidance rates could reach the average set by other mediums and flatten out.

Figure 2: Ad Avoidance by Medium



Demographics

Previous literature on advertising has looked at a variety of demographic data, from age to income. In context of ad avoidance, research is clustered around two demographic aspects: age and gender. Speck and Elliot (1997) looked at the effect of age and found that older respondents were more likely to avoid newspaper advertisements, but less likely to avoid radio or television advertisements (more specifically, younger users are more likely to use technologies to avoid radio and television ads, including remote controls, skip features on VCRs, and channel presets). This suggests that a lack of familiarity with a medium, or at least a lack of familiarity with newer ad avoidance technology, leads to lower ad-avoidance. Other studies suggest older consumers have more advanced heuristic and schema-based processing strategies, which allows them to view more advertisements without becoming overwhelmed (Goodrich, K, 2013). Taken together, this suggests that older internet users are less likely to avoid online advertisements than younger users. Combined with research that indicates consumers are often ambivalent about the benefits and drawbacks of new technology (Bitner, 2002), it is plausible that older users may feel more ambivalent towards ad avoidance technology that is "newer" to them because their soft ad avoidance skills are more entrenched (although they are still subject to the mere exposure effect as explored by Ruggieri and Boca (1994)).

Gender is the other demographic variable that was found to impact ad avoidance. At a high level, women have been found to have more negative attitudes towards advertising across all mediums (Dutta-Bergman MJ, 2006). In context of ad avoidance, Rojas-Mendez, J., Davies, G., & Madran, C. (2008) found that women avoided ads more than their male counterparts across mediums, although the difference was only significant in the UK (the other studied countries were Turkey and Chile). Furthermore, Cleveland (2009) found that gender affected television ad avoidance. Men tended to favor mechanical avoidance (e.g., switching channels) while women favored behavioral avoidance (e.g., talking to someone).

3.2 Advertisement Characteristics

Each advertisement has an array of characteristics that can be used for classification purposes. Common characteristics in past advertising studies include location, movement, size, color, and relevance (Li, H., & Bukovac, J. L, 1999; Jurca, M. A., & Madlberger, M, 2015). However, ad characteristics studied in prominent ad avoidance literature were often less specific and more closely tied to consumer perception. In other words, researchers categorized ads as “annoying” or “confusing” instead of “large” or “flashing”, and studied ad avoidance in relation to those broader ad characteristics. This section looks at the three selected ad characteristics: annoyance, irrelevance, and privacy-invasiveness, beginning with annoyance. These three characteristics repeatedly surfaced as significant drivers of ad avoidance.

Edwards, Li, and Lee (2002) found that higher ad annoyance—as perceived by consumers—leads to higher ad avoidance. Advertisements that disrupt content areas (in the middle of an article) are perceived as more annoying than ads that are in non-content areas (to the side of the page). Furthermore, advertisement design that was seen as “cluttered” due to overcrowding, graphic design, etc. was perceived as more annoying. Cho and Cheon (2004) examined online ad annoyance as well, and found that perceived goal impediment, such as an advertisement disguised as a legitimate search result, was seen as annoying. This result was reinforced by McCoy et al. (2007) and Kelly, Kerr, and Drennan (2010), who discovered that goal impediment not only raises user annoyance, but also increases online ad avoidance.

Another possible explanatory factor is ad relevancy. Edwards et al., (2002) found that ads that are less relevant to the website content led to higher ad avoidance than website-relevant advertisements. Furthermore, advertisements not in line with editorial leanings (i.e. political) led to higher ad avoidance as well. However, others (Simola, J., Kivikangas, M., Kuisma, J., &

Krause, C. M, 2013; McCoy et al, 2007) did not find a significant difference in user perceived intrusiveness when exposed to relevant vs. irrelevant online ads. This result suggests that ad relevance may not be a consistent factor in online ad avoidance, and also implies that ad relevance and ad annoyance share some overlap. At the very least, the effect appears to be contingent, i.e. users feel irrelevant ads are more annoying, and act accordingly. This research applied to online ad-blocking would look at the importance of relevance (both relevance of advertising to the website and the user) in ad-blocking usage.

Privacy is the last selected ad characteristic. Awad and Krishnan (2006) looked at the conflict between internet advertisers who want to offer personalized advertisements and the users who have privacy concerns. Although the research does not address the implications of ad-blocking usage to combat privacy intrusion, it does cover some interesting points. Gaining trust and personal interest are factors advertisers need to consider if they want to have greater data access, and asking explicit permission before gathering data can reduce user resistance. Awad and Krishnan focused on internet usage, but does not directly address ad avoidance to the same degree as research on ad annoyance and ad relevance. A natural extension of the research on ad characteristics would look at the degree to which ad annoyance, relevance, and privacy invasiveness makes users more likely to use ad-blocking software.

3.3 Contribution

Research on the explanatory factors behind ad avoidance has looked at ad characteristics, demographics, and user perceptions. Research has also been done on low user adoption factors, which could play a role in the relatively low usage rate of ad-blocking software. However, only some of this research is non-internet specific. The key gap my research addresses is whether the same ad-avoidance factors that play a role in offline ad avoidance apply to the more intensive process of installing ad-blocking software. My research also attempts to differentiate the relative importance of the explanatory factors in online ad avoidance and explore the reasons why ad-blocking usage is relatively low.

4. Methodology

The usage of ad-blocking software is a rapidly growing trend (Beck, 2013) that primarily interests websites and advertisers because of their revenue model (Enders et al., 2008). The study focused on testing the relationships between ad characteristics, demographics, ad-blocking usage, and whitelisting. These relationships give insight into the primary issues websites face, including key drivers of ad-blocking usage and effectiveness of various mitigation techniques. This section will introduce my hypotheses, survey design, and study limitations.

4.1 Hypotheses

Previous research indicates that the majority of media consumers find advertisements intrusive, regardless of structure, presentation, or media type (Cho et al., 2004). Further research has shown that ads which are more intrusive lead to higher consumer avoidance (Edwards et al., 2002). However, research also found that although all advertisements are intrusive, some ad characteristics are more intrusive than others (Kelly, L., Kerr, G., & Drennan, J, 2010). Cho found that perceived goal impediment was the largest driver of ad avoidance, which falls within the "annoyance" category laid out by Speck and Elliot (1997). This leads to the first hypothesis:

> *Hypothesis I: Annoyance will be a stronger driver of ad-blocking usage relative to the other identified ad characteristics, i.e. Irrelevance and Privacy invasiveness*

Consumers find ads that use personal data (such as location-targeted advertising) more intrusive than similar ads that do not violate their perceived privacy (Awad et al., 2006). Previous research has shown that among internet users, a clear grouping can be made between users who are not concerned about their privacy, and users who are very concerned (Sheehan, 2011). Although consumers also find irrelevant ads more intrusive than relevant ads (Edwards et al., 2002) the strictly divided grouping does not appear in previous literature for users concerned about annoyance or relevance of advertisements. Because online consumers who are concerned about ads violating their privacy tend to be very concerned (Sheehan, 2011), which will lead to a difference in response to whitelisting. For example, even if a website may shut down unless its users whitelist (elect to view ads on the site), the privacy focused consumer may have a stronger objection based on their strong tendency towards anonymity. This leads to the hypothesis:

Hypothesis II: Privacy invasiveness will be a stronger limiter of whitelisting likelihood relative to the other selected ad characteristics, i.e. Annoyance and Irrelevance

Demographics are an explanatory factor (Speck and Elliot, 1997) that is likely relevant to ad-blocking usage. Previous research found that familiarity with a medium leads to increased ad avoidance (Speck et al., 1997). Younger online users should be on average be more familiar with the internet, as employed, higher educated, and older users tend to spend less time per day online, although the gap is narrowing (van Deursen and Van Dijk, 2014). Furthermore, other literature has indicated that consumers are often ambivalent about the benefits and drawbacks of new technology (Bitner, 2002). Ad-blocking software may not fall under the "new technology" label for younger users who have peers that use ad-blocking software. This leads to the hypothesis:

Hypothesis III$_A$: Younger users are more likely to use ad-blocking software

Gender was found to affect television ad avoidance (Cleveland et al., 2009). Men tended to favor mechanical avoidance (e.g., switching channels) while women favored behavioral avoidance (e.g., talking to someone). I posit that installing ad-blocking software fall under the mechanical avoidance spectrum. This leads to the hypothesis:

Hypothesis III$_B$: Use of ad-block will be higher among men relative to women

Ad-blocking technology is relatively new, and requires more effort than other ad avoidance techniques. Previous research has found that some individuals do not always act rationally when faced with a delayed gratification decision (Mischel and Ebbesen, 1972; Wood, 1998; Liu, Li, and Hu, 2013). Wittmann and Paulus (2008) found that many individuals have a distorted view of the cost of time, and weight short-term results heavily. They also found that many individuals tend to overestimate the duration of time intervals. As a result, these individuals tend to act illogically when faced with decisions that have short-term costs but long-term gain. This research is applicable to ad avoidance and ad-blocking because many internet users may be overweighting the short-term costs of not installing ad-blocking software. The time it takes to learn about and install ad-blocking software is minimal, but users may not be properly evaluate the difference in short-term time spent vs. long-term time saved. Over one year, an ad-block user could save several hours stemming from lack of video advertisements, which easily eclipses the initial installation time, but many consumers may not be analyzing the times objectively. Research has also shown that consumers are often ambivalent about the benefits and drawbacks of new technology (Bitner, 2002). Ad-blocking technology is relatively new and unknown; mass internet ad-blocking solutions were not available five years ago. Given this information, I posit that exposure to educational information about ad-blocking technology, such as average time to install, proposed benefits, and average ease of use would improve the likelihood of usage, as usage may be held back due to delayed gratification psychology and fear of new technology. This leads to the final hypothesis:

Hypothesis IV: Exposure to educational information regarding ad-blocking technology will increase consumer interest in ad-blocking software

4.2 Supporting Data

I tested the above hypotheses using data from a consumer survey. Below, I outline the survey design, demographics, and data collected. I also cover the specific links between the hypothesis and the data, and the limitations of the survey.

4.2.1 Research Design

Data for this study was collect on Amazon's Mechanical Turk platform in January 2015. The survey covered a variety of topics, ranging from rating the annoyance level of ads demonstrated through visuals to evaluating hypothetical whitelisting situations. Evaluation questions were structured using a Likert scale (1 = Strongly disagree, 5 = Strongly agree). The questions in the survey were designed to gather the data needed to evaluate my hypotheses.

The survey responders were all Master level, which is a designation given by Amazon to MTurk users who have a long history of accurate and high-level responses on MTurk. The Master MTurk users answer surveys and perform small tasks for minor monetary compensation. There were 70 responders in total with a somewhat atypical demographic breakdown compared to the average internet user (see Table 1.1 for comparison). Table 1 and Figure 2 show the basic demographic data.

Table 1: Survey demographic data

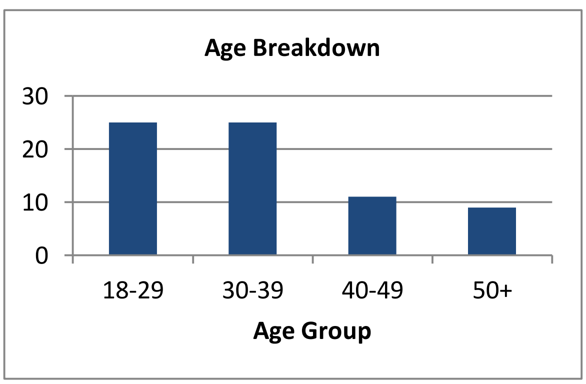
	Number	Percentage
Age		
18-29	25	36%
30-39	25	36%
40-49	11	16%
50+	9	13%
Total	70	
Gender		
Male	48	69%
Female	22	31%
Ad-block Usage		
Yes	49	70%
No	21	30%

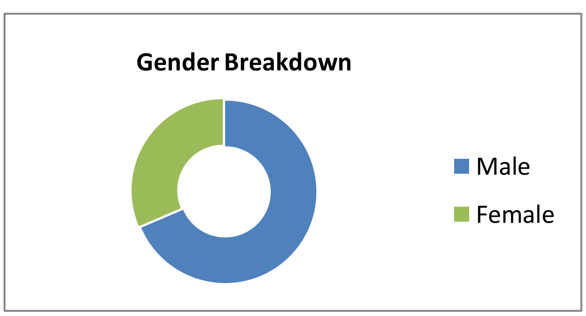
Table 1.1: US Internet user demographic data

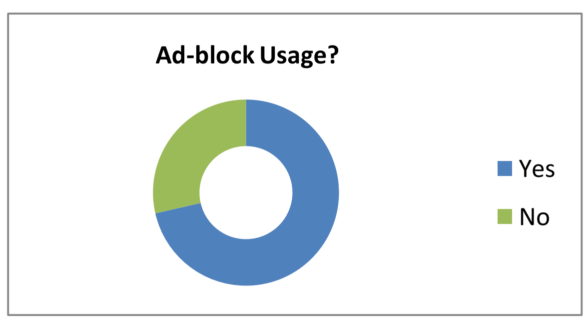
	Number w/Internet (millions)	Percentage
Age		
18-34	56,752	23 %
35-44	33,198	13%
45-64	65,951	27 %
65+	27,750	11%
Total (incl. 0-17)	243,398	100.00%
Gender		
Men		87%
Women		86%

Sources: Pew Research Center, Internet User Demographics, 2014; US Census, Computer and Internet Use in the United States, 2013.

Figure 3: Visualized survey demographics







The male/female gender distribution does not match the general internet demographic breakdown, with males and younger users being overrepresented. Ad-blocking usage is also far outside the general demographic breakdown. Estimates place general ad-blocking usage at under 10% of users (Beck, 2013) but survey respondents had 70% usage.

4.2.3 Measures and Variables

The data needed to evaluate my hypotheses was collected at various points in the survey. Early in the survey, respondents were identified as either ad-block users, or non-ad-block users. Both populations were then asked to rate how annoying/irrelevant/privacy-invasive they found various types of advertisement on a 5-point Likert scale. This data was used to evaluate Hypothesis I. The survey then moved to a section on whitelisting, which tested potential responses to whitelist strategies. Taken with earlier data on ad-blocking usage, this was sufficient to evaluate Hypothesis II. Data was also gathered on the demographics of the respondents, including age and gender. This provided the data needed to evaluate Hypothesis III. The key variables for Hypotheses I-III are shown in Table 2.

Table 2: Key Variables for Hypotheses I-III

	Annoyance	Irrelevance	Privacy-invasiveness	Whitelisting
Average	3.864	4.014	3.751	3.271
Standard Deviation	0.658	0.892	0.775	0.845
Min	1.875	1.500	2.000	1.400
Max	5.000	5.000	5.000	5.000

The non-ad-block users were asked to rate their interest in ad-blocking software. They were then shown an overview of ad-blocking technology and were then asked to again rate their interest. This data was used to evaluate Hypothesis IV. The key variables (before and after interest levels) for Hypothesis IV are shown in Table 3.

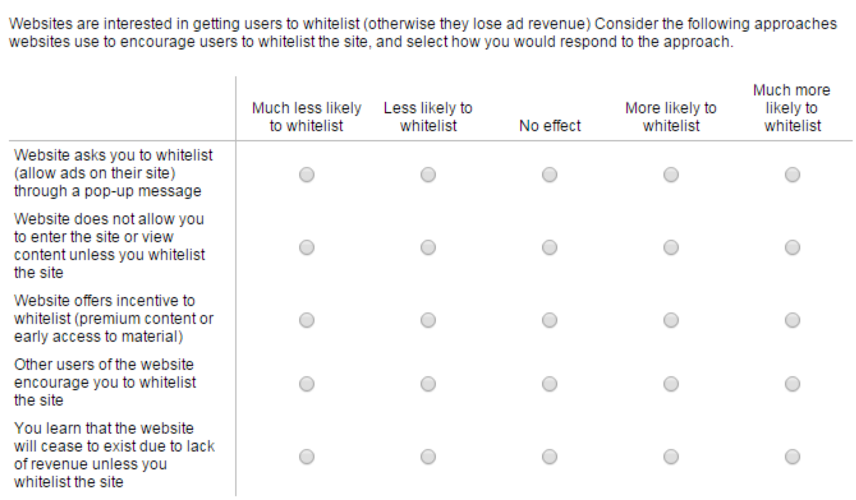
Table 3: Key Variables for Hypothesis IV

Statistic	*Before (5 point Likert scale)*	*After (5 point Likert scale)*
Interest level in ad-blocking software (mean)	2.955	3.5
Standard Deviation	0.975	0.988
Min	1	1
Max	4	5

The key variables highlighted in the previous tables were gathered through survey questions designed to test how users would react in a real-life situation. Users might react abnormally to a fake website used for testing purposes, so questions relied on descriptive scenarios. Example whitelisting and ad characteristics questions are shown in Figure 4.

Figure 4: Sample Survey Questions and Measurements

Whitelisting Questions


Websites are interested in getting users to whitelist (otherwise they lose ad revenue) Consider the following approaches websites use to encourage users to whitelist the site, and select how you would respond to the approach.

	Much less likely to whitelist	Less likely to whitelist	No effect	More likely to whitelist	Much more likely to whitelist
Website asks you to whitelist (allow ads on their site) through a pop-up message					
Website does not allow you to enter the site or view content unless you whitelist the site					
Website offers incentive to whitelist (premium content or early access to material)					
Other users of the website encourage you to whitelist the site					
You learn that the website will cease to exist due to lack of revenue unless you whitelist the site					

Sample Relevance Question

Please view the following article.

IT'S NOT JUST THE ALCOHOL TALKING

THE ONLY BEER IN TOWN

By: Derek Harrison

Windsor is comfortably tucked between Southern Ontario and Michigan, two major forces in the craft beer world. Michigan alone sports over 200 breweries, while Ontario has caught up to and surpassed the more traditionally beery provinces to the east in variety, quality and enthusiasm. Yet somehow, until last September, we had no brewery of our own, not even a specialty beer bar.

proper, only a half-wall partitioning the two. We spotted Ryan up ahead, busy mingling with a tour group a dozen-or-so strong.

The Beer

While we waited, the bartender/receptionist showed us to a seat in the taproom and poured us a taster each of their three tapped beers. We started with the Kölsch, a German-style lagered pale ale at 4.5%. It was refreshing, light and hoppy but not bitter. It could make for an excellent gateway craft beer; better and more flavourful than the standard corporate fare but not a radical departure from it either.

Following the Kölsch was the amber lager, often known simply as "Walkerville." It's their original beer and the only vestige remaining from the former incarnation of the brewery. The

burger's line of house-brewed beers, new lakeside brewer The Lonsbery Brewing Co. in the planning, and Chris Ryan's Walkerville, which will be remembered as the first craft brewery in Windsor.

The Craft Beer Renaissance in Ontario

While craft beer is enjoying a renaissance all over the world, the transformation in North American has been especially extreme. Prohibition wiped out variety and craftsmanship in one fell swoop. Only the largest breweries survived, and the ramifications were

ville in 1956. The original brewery was demolished in 1962. Carling was later bought by Coors, which in turn merged with Molson.

In the 70s the number of breweries in North America was at an all-time low. But when one of the last vestiges of Prohibition, the law against homebrewing, was repealed in 1979, things began to change. Suddenly, all the closet brewers who were privately drinking illegal, full-flavoured beers were finally able to go public and start sharing the love. Since then the number of American breweries has climbed from less than 100 to more than 2,500.

Now please view the modified article.

IT'S NOT JUST THE ALCOHOL TALKING

THE ONLY BEER IN TOWN

By: Derek Harrison

Windsor is comfortably tucked between Southern Ontario and Michigan, two major forces in the craft beer world. Michigan alone sports over 200 breweries, while Ontario has caught up to and surpassed the more traditionally beery provinces to the east in variety, quality and enthusiasm. Yet somehow, until last September, we had no brewery of our own, not even a specialty beer bar.

proper, only a half-wall partitioning the two. We spotted Ryan up ahead, busy mingling with a tour group a dozen-or-so strong.

The Beer

While we waited, the bartender/receptionist showed us to a seat in the taproom and poured us a taster each of their three tapped beers. We started with the Kölsch, a German-style lagered pale ale at 4.5%. It was refreshing, light and hoppy but not bitter. It could make for an excellent gateway craft beer; better and more flavourful than the standard corporate fare but not a radical departure from it either.

Following the Kölsch was the amber lager, often known simply as "Walkerville." It's their original beer and the only vestige remaining from the former incarnation of the brewery. The

burger's line of house-brewed beers, new lakeside brewer The Lonsbery Brewing Co. in the planning, and Chris Ryan's Walkerville, which will be remembered as the first craft brewery in Windsor.

The Craft Beer Renaissance in Ontario

While craft beer is enjoying a renaissance all over the world, the transformation in North American has been especially extreme. Prohibition wiped out variety and craftsmanship in one fell swoop. Only the largest breweries survived, and the ramifications were

ville in 1956. The original brewery was demolished in 1962. Carling was later bought by Coors, which in turn merged with Molson.

In the 70s the number of breweries in North America was at an all-time low. But when one of the last vestiges of Prohibition, the law against homebrewing, was repealed in 1979, things began to change. Suddenly, all the closet brewers who were privately drinking illegal, full-flavoured beers were finally able to go public and start sharing the love. Since then the number of American breweries has climbed from less than 100 to more than 2,500.

How intrusive did you find the ESPN Radio ad compared to the Walkerville Brewery ad?

	Much Less Intrusive	Less Intrusive	No difference	More Intrusive	Much More Intrusive
I found it:	○	○	○	○	○

4.3 Analysis

This section describes how the hypotheses were tested using t-tests and logistic and linear regression. Three regressions were used to test the first three hypothesis, and t-tests were used to test the last two hypothesis.

To determine if annoyance is a stronger driver of ad-blocking usage relative to the other ad characteristics as posited in Hypothesis I, an intrusiveness rating for each ad characteristic was created. These indexes were based on several questions rated on a Likert scale. For example, the irrelevance index was formed by asking users how intrusive they found ads that were irrelevant to their interests or irrelevant to a hypothetical site. A logistic regression was run to measure if any of the ad characteristics significantly increased ad-blocking usage.

Probability (Ad-blocking Usage) $= \beta 0 + \beta 1 Annoyance + \beta 2 Irrelevance + \beta 3 Privacy + \varepsilon$

The ad-blocking usage dependent variable measures present or past usage of ad-blocking software as a binary variable. The three independent variables are indexes that measure feelings of intrusiveness from annoying, irrelevant, and privacy-invasive ads respectively.

However, the regression did not directly address the original hypothesis as it requires comparison of ad characteristics. If any of the ad characteristics significantly increased ad-blocking usage, the next step was to compare the relative significance of ad characteristics directly. In order to do this, t-values comparing the average intrusiveness of ad characteristics were calculated. Corresponding p-values from the t-values were used to identify if certain ad characteristics were statistically stronger drivers of ad-blocking usage. This assessed support in terms of beta (relative size) of the ad characteristics, which was the original hypothesis.

Hypothesis II posits that Privacy invasiveness is a stronger limiter of whitelisting likelihood relative to the other selected ad characteristics. This hypothesis was first evaluated to measure whether ad indexes of privacy, annoyance, and relevance significantly affect the chance of an individual whitelisting a website using a linear regression model.

$$\textit{Willingness to whitelist} = \beta 0 + \beta 1 \textit{Intrusiveness} + \beta 2 \textit{Relevance} + \beta 3 \textit{Privacy} + \varepsilon$$

The willingness to whitelist dependent variable measures users' willingness to whitelist a website, measure on an index of hypothetical situations, on a 5-point Likert scale. The three independent variables are indexes that measure feelings of intrusiveness from annoying, irrelevant, and privacy-invasive ads respectively.

Once again, the regression did not directly address the original hypothesis as it requires comparison of ad characteristics. If any of the ad characteristics significantly increased whitelisting likelihood, the next step was to compare the relative significance of ad characteristics directly. In order to do this, t-values comparing the average effect each ad characteristic had on whitelisting likelihood was calculated. Corresponding p-values from the t-values were used to identify if certain ad characteristics were statistically stronger drivers of whitelisting likelihood.

In order to test if use of ad-block is negatively related to age (in other words, if younger users are more likely to use ad-blocking software), a logistic regression was run. Each age group was converted to a binary independent variable in the regression model. To assess the hypothesis, the 50+ age group was used as a control group. The other three age groups were measured against the control group to test for significant differences in ad-blocking usage between younger age ranges and the oldest age range.

Probability (Ad-block Usage) = β0+ β1Age18-29 + β2Age30-39+β3Age40-49+ β4Age50+ε

In order to test Hypothesis III_B which posits that use of ad-block is higher among men relative to women, a proportion t-test was used because the dependent variable (ad-blocking usage) was measured in binary. First, the sample proportion ($\hat{p}$) of total respondents who use ad-block was calculated. A standard deviation for the sample proportion was calculated. A z-score was calculated for each gender using this standard deviation and the previous proportion statistics.

$$\hat{p} = \frac{n_m P_m + n_f P_f}{n_m + n_f}$$

$$\sigma = \sqrt{\hat{p}(1-\hat{p})(\frac{1}{n_m} + \frac{1}{n_f})}$$

$$z = \frac{(P_m - P_f) - 0}{\sigma}$$

Using the calculated z-scores, a p-value was calculated to see if average ad-blocking usage varied significantly by gender.

To evaluate if exposure to educational information regarding ad-blocking technology is positively correlated with consumer interest in ad-blocking software for Hypothesis IV, a two-sample t-test (paired because the population was the same) was used to determine if there was a significant increase in user interest (in the non-ad-block population) before and after learning more about ad-blocking software.

4.4 Appropriateness and Limitations

The strengths of the approach include the survey respondent base. Heavy internet users (see Section 5) made up a high percentage of the respondents, which is a segment that websites analyzing ad-block usage are interested in curtailing (Rauline, 2014). The approach also ensured that users were responding to questions about online advertisements in an online environment, making the hypothetical situations more realistic.

Limitations include the difficulty of recreating an accurate advertising atmosphere. For example, describing an advertisement that disrupts a website from loading may not have the same effect on a user as an actual disruptive advertisement. Another limitation in my first hypothesis testing is ad-blocking users could be more (or less) annoyed by ads because they rarely see them, not because of basic like or dislike. The novelty factor may be the reason for the stronger dislike of advertisements, rather than a reason why they may have downloaded ad-blocking software.

5. Results

As described in the methodology section, t-tests, linear regression, and logistic regression models were used to test the hypotheses. Overall, mixed support for the hypotheses was found. Before reviewing support for the hypotheses, descriptive statistics on internet usage from the survey will be discussed to improve the context of the formal results.

45% of respondents spend between 4-6 hours online per day, which falls under moderate internet usage, with nearly another 40% spending 7+ hours a day, which is classified as heavy internet usage (Aboujaoude and Starcevic, 2008). Roughly 90% of respondents also use Firefox or Chrome as their primary web browser, which may partially explain the higher than average usage of ad-blocking software. Firefox and Chrome are considered the easiest browsers to install ad-blocking software on, and have the highest percentage of ad-blocking users (Yablonka, 2014).

Survey results indicated that ad-blocking software was considered easy to install. Over 70% of respondents who have used ad-blocking software said that installing ad-blocking software was "Not Difficult." More tellingly, roughly 60% said that the first time they set up an ad-blocking solution, it took them between zero and five minutes. 10% said that it took them more than ten minutes, and 5% said it took more than thirty, showing that although the average difficulty of installation is low, it may be highly difficult if a consumer lacks a certain level of tech-savvy.

Respondents were also given an explanation of whitelisting, and asked how likely they were to whitelist a website given a variety of approaches. For example, respondents were asked if they would be more or less likely to whitelist a site if the website did not allow them to view content until the disabled their ad-blocking software. Respondents indicated that the most effective methods to encourage whitelisting would be if a website offered an incentive to whitelist (such as premium content or early access) or if users of the website asked other users to whitelist. On the other hand, the least effective methods are directly asking users to whitelist the site and blocking users from entering the site if they have an ad-blocker.

Finally, users who have never used ad-blocking software were asked to rate how important several reasons were for their non-use. "Lack of awareness of ad-blocking software" was overwhelmingly the number one reason, with "Privacy concerns" and "Perceived difficulty installing ad-blocking software" following up.

5.2 Hypothesis I Results

Hypothesis I tested if annoyance is a stronger driver of ad-blocking usage relative to the other selected ad characteristics (relevance and privacy). A logistic regression was used to test this hypothesis because the dependent variable (ad-blocking usage) was a binary variable. The initial regression model seen in Figure 4 measured the strength of ad characteristics relative to ad-blocking usage. A significance level of 0.05 was used to test if any of the ad characteristics significantly increased ad-blocking usage, but unfortunately no significance was found as seen in Table 4. Thus, directly comparing the ad characteristics was skipped because none were significant.

Table 4: Hypothesis I Model Parameters

Ad Characteristic	Value	Standard error	Pr > Chi²	Odds Ratio
Annoyance Index	0.261	0.193	0.177	2.052
Relevance Index	-0.041	0.173	0.815	0.921
Privacy Index	-0.193	0.189	0.308	0.637

The regression controlled for the three ad characteristics. To test Hypothesis I without controlling for all independent variables, three separate logistic regressions were run. A significance level of 0.05 was used once again to test if any of the ad characteristics significantly increased ad-blocking usage, and the results showed higher p-values than the first regression. This is likely due to the covariance between the independent variables. Because the three independent variables moved in tandem to a high degree, the controlled regression showed an amplified overall increase in ad-blocking usage.

5.3 Hypothesis II Results

Hypothesis II tested if privacy is a stronger driver of whitelisting usage relative to the other selected ad characteristics. A linear regression was used to test this hypothesis; the regression model can be seen in Figure 5. A significance level of 0.05 was used to test if any of the ad characteristics significantly decreased the likelihood of whitelisting. As seen in Table 5, no significance was found.

Table 5: Hypothesis II Model Parameters

Ad Characteristic	Value	Standard error	t	Pr > |t|
Annoyance Index	0.162	0.213	0.762	0.450
Relevance Index	-0.097	0.183	-0.531	0.598
Privacy Index	-0.289	0.192	-1.505	0.139

Directly comparing the ad characteristics was skipped because the results would be meaningless given the lack of statistical significance of ad characteristics in predicting whitelisting. To test Hypothesis II without controlling for all independent variables, three separate linear regressions were run. A significance level of 0.05 was used once again to test if any of the ad characteristics significantly decreased the likelihood of whitelisting. None of the ad characteristics met the 0.05 cut off, but privacy was close, with one-tail p-value of 0.0595 as seen in Table 6.

Table 6: Hypothesis II Model Parameters – Privacy Independent Regression

Ad Characteristic	Value	Standard error	t	Pr > t (one-tail)
Privacy Index	-0.228	0.144	-1.589	0.0595

5.4 Hypothesis III Results

Hypothesis III_A tested if use of ad-block decreases as age increases. Figure 6 shows the logistic regression that measured if use of ad-block varied significantly between age groups, using the 50+ age group used as the control. The significance level was set at 0.05. The logistic regression found that there was a significant difference in ad-blocking usage between the 18-29 age group and the control group, and the 30-39 age group and the control group. Furthermore, likelihood of usage in the 18-29 age group was higher than the 30-39 age group, and the 30-39 age group had a higher likelihood than the 40-49 age group, supporting Hypothesis III_A. Table 7 shows the coefficient data.

Table 7: Hypothesis III_A Model Parameters

Age Group	Value	Standard error	Pr > Chi²
18-29	0.769	0.256	0.003
30-39	0.635	0.245	0.010
40-49	0.288	0.202	0.153
50-59	0.000	0.000	

Hypothesis III_B tested if use of ad-block was higher among men relative to women. This hypothesis was tested at a significance level of 0.05. Instead, proportion of each population (male, female, and total) that used ad-blocking was calculated. P-values were calculated using a proportion t-test, and no significance was found. In fact, ad-blocking usage among women was higher than ad-blocking usage among men.

Table 8: Two-sample t-test results for Ad-Block Usage by Gender (Hypothesis III_B)

Statistic	*Male*	*Female*	*Other*	*Interpretation*
Proportion	58.33%	68.18%		
Observations	48	22		
P hat			0.614	
Std Dev			0.125	
Z-Score			-0.786	
P-Value - one tail			0.105	No Support For Hypothesis III_B
				Not significant in either direction

5.1 Hypothesis IV Results

Hypothesis IV tested if exposure to educational information regarding ad-blocking technology is positively correlated with consumer interest in ad-blocking software. This hypothesis was tested using a significance level (alpha) of 0.05, which indicates that results are assessed as supporting the hypothesis if there was only a 5% chance or less of being incorrect. As seen in Table 3, the mean consumer interest level rose by more than 0.5 points on the 1-5 Likert scale after a brief explanation of ad-blocking software, from 2.955 to 3.500. In other words, the average consumer interest rose from “Moderate” to “Moderately High”. The one-tail t-test returned a p-value of 0.001, well under the significance level of 0.05, indicating that the increase in consumer interest after learning about ad-blocking software was significant. Thus, Hypothesis I is supported. The following table shows the two-sample t-test results.

Table 9: Two-sample t-test result for Ad-blocking Education (Hypothesis IV)

Statistic	*Before*	*After*	*Interpretation*
Mean	2.955	3.500	
Variance	0.998	1.024	
Observations	22	22	
t Stat	3.464		
P(T<=t) one-tail	0.001		Support Hypothesis IV

6. Discussion

This paper addresses the research gap on the drivers of ad-blocking and whitelisting by showing that demographics play a significant role in ad-blocking use, and ad characteristics are not key drivers of ad-blocking or whitelisting activity. Only two out of the five hypotheses were supported, but the hypotheses that were not supported still provide valuable insight for websites and advertisers, and outline a path for future research.

The results of the two-sample paired t-tests showed there is a significant increase in consumer interest after learning about ad-blocking software. In addition, over 90% of survey respondents (who have not used ad-block) indicated that "lack of awareness" was a major or minor factor in their non-use of adblock, a much higher percentage than any other factor. This suggests that most non ad-block users are both receptive to the idea of ad-blocking software and do not have major moral or privacy concerns with using ad-blocking software that would limit adoption. This is a discouraging result for advertisers and websites, and indicates that ad-blocking usage will continue to grow quickly as awareness spreads. As ad-block transitions from niche to mainstream, the ad-based revenue model most websites employ could be badly damaged. The survey also showed that perceived difficulty and time taken to install ad-blocking software was a barrier. As previous literature shows, this is a common obstacle but can be overridden if the long-term benefits of ad-block usage are made clear to the user (Wittmann and Paulus, 2008).

Ad characteristics were ultimately not important drivers of ad-block or whitelisting, despite the prominence of ad characteristics in previous research. The lack of impact is likely due to the unique nature of ad-blocking software compared to other ad avoidance techniques studied in past research. Users who change a TV channel to avoid an annoying ad are reacting to a specific ad, and that ad's characteristics. However, according to the survey users install ad-blocker mainly because they have recently learned about it through friends or a forum, not because of a specific ad or because they found online ads intrusive in general. In the same vein, the survey showed that for most users, the decision to whitelist is website specific. Users who value a website are likely to whitelist it, regardless of the ads that website runs. For advertisers and websites, this means that making ads less annoying, more relevant, or less privacy invasive is likely futile. Users are not going to whitelist a website (or not install ad-block) no matter how non-intrusive the ads. Websites badly affected by ad-blocking should focus on coming up with alternative strategies. Survey responses indicated that users are most likely to whitelist if they are given an incentive to do so (such as early access to content), if other users on the site ask them to, or if the website is going to shut down unless advertising revenue increases. Of course, ad characteristics may not have been statistically significant drivers because of range restriction within the survey. The standard deviation of all three ad characteristic indexes was low, indicating the survey may not have accurately replicated the gap between, for example, annoying and non-annoying ads in the eyes of respondents, leading to range restriction.

Age was shown to be a significant factor in ad-blocking usage. This reflects the factors indicated in the literature review, such as higher familiarity with certain mediums and more advanced processing heuristics that older users have. It seems likely that the significance of age is also tied to the ways users are learning about ad-blocking software. As mentioned above, most users install ad-blocker because they learned about it through friends or an online forum/chatboard. Younger internet users are more likely to have friends that use ad-block, simply because internet usage is higher among younger demographics, and are also more likely to use online forums (Madden et al., 2013).

A surprising result was the impact of gender on ad-blocking usage. Use of ad-block was actually higher among women relative to men, although the difference did not meet statistical significance. This could indicate that ad-blocking software falls centrally in the mechanical avoidance spectrum. Women may potentially have larger social circles to learn about ad-blocking software (Kurtosi, Z, 2004), or find ads more intrusive. Due to the relatively small sample size, this result is far from conclusive and should be retested before future research is conducted.

7. Conclusion

This paper contributes to existing research by applying ad avoidance factors to online ad-blocking and whitelisting, and shows that age and exposure are significant drivers of ad-blocking usage. Although the link between ad characteristics and ad-blocking/whitelisting was not supported, the results provide guidance for websites looking for ways to increase whitelisting. The unexpectedly higher usage of ad-block among women relative to men was also uncovered by this paper, and is a possible avenue for future research. Future research could also build off the age results from this paper. It would be interesting to know if social networks are driving ad-blocking usage among younger users, and if the age results found in this paper will still hold true in the future. Other paths for future research include the future of ad-blocking on mobile, where resistance from firms is much stronger, or attempting to quantify the financial impact of ad-blocking on a variety of websites.

Using the results in this paper should be done with caution. The survey did not perfectly recreate the various types of advertisements encountered during every day internet usage. The average user of the survey was young, male, and tech-savvy, which potentially limits the transferability of this paper's results. Users who already use ad-blocking software rarely see internet advertisements, which could have affected their impression of ad characteristics and cause them to perceive every ad as highly intrusive. Finally, the survey was self-reported (leading to less control of biases than an experimental methodology) and the sample size was relatively low (weakening the statistical analysis of the paper).

Despite these limitation, this paper took important steps in proving which factors affect online ad-blocking usage, and which factors do not. In addition, this paper and future research on ad-blocking will be useful for players in the commercial space. The results suggest that ad-blocking will be increasingly important in the near future. Websites attempting to adjust their ad-based revenue model now know that ad characteristics are not a significant factor, and demographics can significantly impact their risk level.

Bibliography

Awad, N., & Krishnan, M. S. (2006). The personalization privacy paradox: an empirical evaluation of information transparency and the willingness to be profiled online for personalization. MIS Quarterly, 30(1), 13-28.

Barnard, J. (2013). Advertising Forecasts June 2013. Publicas Groupe & ZenithOptimedia.

Batterham, P. J. (2014). Recruitment of mental health survey participants using Internet advertising: content, characteristics and cost effectiveness. International Journal Of Methods In Psychiatric Research, 23(2), 184-191. doi:10.1002/mpr.1421

Bitner, M. J., Brown, S. W., & Meuter, M. L. (2000). Technology infusion in service encounters. Journal of the Academy of marketing Science, 28(1), 138-149.

Bornstein, R. F., & D'Agostino, P. R. (1994). The attribution and discounting of perceptual fluency: Preliminary tests of a perceptual fluency/attributional model of the mere exposure effect. Social Cognition, 12(2), 103-128.

Cho, C.-H., & as- University of Texas at Austin). (2004). Why Do People Avoid Advertising on the Internet? Journal of Advertising, 33(4), 89–97.

Cleveland, M., Laroche, M., Papadopoulos, N., Berács, J., Elliott, S., Hallberg, A., ... & Verma, B. (2009, June). Identity, Demographics, And Consumption: A Study of Segmentation Variables across Eight Countries and Nine Product Categories. In ASAC (Vol. 30, No. 3).

Dahlén, M., & Edenius, M. (2007). When is advertising advertising? Comparing responses to non-traditional and traditional advertising media. Journal of Current Issues & Research in Advertising, 29(1), 33-42.

Dix, S., & Phau, I. (2010). Television Advertising Avoidance: Advancing Research Methodology. Journal Of Promotion Management, 16(1/2), 114-133. doi:10.1080/10496490903574013

Dutta-Bergman MJ. (2006). The demographic and psychographic antecedents of attitude toward advertising. J Advert Res; 46(1):102–12.

Edwards, S. M., Li, H., & Lee, J.-H. (2002). Forced Exposure and Psychological Reactance: Antecedents and Consequences of the Perceived Intrusiveness of Pop-Up Ads. Journal of Advertising, 31(3), 83–95.

Enders, A. (2008). Overview of the digital transformation of the UK creative economy. Bain & Company.

Gonzalez, N. (2013) “Half of Destructoid’s readers block our ads. Now what?” Destructoid.

Goodrich, K. (2013). Effects of age and time of day on Internet advertising outcomes. Journal Of Marketing Communications, 19(4), 229-244. doi:10.1080/13527266.2011.620618

Heath, R. (2005) Cut through Ad Avoidance. Radio Advertising Bureau Studies & Clarke Chapman Research.

Hervet, G., Guérard, K., Tremblay, S., & Chtourou, M. S. (2011). Is banner blindness genuine? Eye tracking internet text advertising. Applied Cognitive Psychology, 25(5), 708-716. doi:10.1002/acp.1742

Jurca, M. A., & Madlberger, M. (2015). Ambient advertising characteristics and schema incongruity as drivers of advertising effectiveness. Journal of Marketing Communications, 21(1), 48-64.

Kelly, L., Kerr, G., & Drennan, J. (2010). Avoidance of advertising in social networking sites: The teenage perspective. Journal of Interactive Advertising, 10(2), 16-27

Kurtosi, Z. (2004) Aspects of gender in social networks. *Szeged University Working Paper.*

Liu, Y., Li, H., & Hu, F. (2013). Website attributes in urging online impulse purchase: An empirical investigation on consumer perceptions. *Decision Support Systems*, *55*(3), 829-837

Madden, M., Lenhart, A., Duggan, M., Cortesi, S., & Gasser, U. (2013). *Teens and technology 2013*. Washington, DC: Pew Internet & American Life Project.

McCoy, S., Everard, A., Polak, P., & Galletta, D. F. (2007). The effects of online advertising. Communications of the ACM, 50(3), 84-88.

Mischel, W., Ebbesen, E. B., & Raskoff Zeiss, A. (1972). Cognitive and attentional mechanisms in delay of gratification. *Journal of personality and social psychology*, *21*(2), 204.

Nelson, L. D., Meyvis, T., & Galak, J. (2009). Enhancing the Television-Viewing Experience through Commercial Interruptions. Journal of Consumer Research, 36(2), 160-172.

Olney, T. J., Holbrook, M. B., & Batra, R. (1991). Consumer Responses to Advertising: The Effect of Ad Content, Emotions, and Attitude toward the Ad on Viewing Time. Journal Of Consumer Research, 17(4), 440-453.

Rauline, N. (2014). French publishers willing to prosecute ad blockers. *Les Echos*.

Rojas-Mendez, J., Davies, G., & Madran, C. (2008). Universal differences in advertising avoidance behavior: A cross-cultural study. Journal of Business Research, 62, 947-954.

Rosengren, S., & Dahlén, M. (2013). Judging a Magazine by Its Advertising: Exploring the Effects of Advertising Content on Perceptions of a Media Vehicle. Journal of Advertising Research, 53(1), 61-70.

Ruggieri, S., & Boca, S. (2013). At the roots of product placement: the mere exposure effect. Europe's Journal of Psychology, 9(2), 246-258.

Sheehan, K. B., & Hoy, M. G. (2000). Dimensions of privacy concern among online consumers. *Journal of public policy & marketing*, *19*(1), 62-73.

Siddarth, S., & Chattopadhyay, A. (1998). To zap or not to zap: A study of the determinants of channel switching during commercials. Marketing Science, 17(2), 124-138.

Simola, J., Kivikangas, M., Kuisma, J., & Krause, C. M. (2013). Attention and Memory for Newspaper Advertisements: Effects of Ad-Editorial Congruency and Location. Applied Cognitive Psychology, 27(4), 429-442. doi:10.1002/acp.2918

Speck, P. S., & Elliott, M. T. (1997). Predictors of Advertising Avoidance in Print and Broadcast Media. Journal of Advertising, 26(3), 61–76.

Teixeira, T. (2014). The Rising Cost of Consumer Attention: Why You Should Care, and What You Can Do about It. Harvard Business School Working Paper.

Tse, A. C. B., & Lee, R. P. (2001). Zapping behavior during commercial breaks. Journal of Advertising Research, 41(3), 25-30.

van Deursen, A. J., & Van Dijk, J. A. (2014). The digital divide shifts to differences in usage. New Media & Society, 16(3), 507-526.

Wittmann, M., & Paulus, M. P. (2008). Decision making, impulsivity and time perception. Trends in cognitive sciences, 12(1), 7-12.

Wood, M. (1998). Socio-economic status, delay of gratification, and impulse buying. *Journal of economic psychology*, *19*(3), 295-320

Yablonka, I. (2014). Ad Block Report. Clarity Ray Annual Report.

Yoonjae, N., Kyonghee H., K., & Sungjoon, L. (2010). Does It Really Matter That People Zip through Ads? Testing the Effectiveness of Simultaneous Presentation Advertising in an IDTV Environment. Cyberpsychology, Behavior & Social Networking, 13(2), 225-229. doi:10.1089/cyber.2009.0115