**This document is published in:**

**Expósito-Ventura, M., Ruipérez-Valiente, J. A., & Forné, J. (2020, June). Measuring online advertising viewability and analyzing its variability across different dimensions. In Proceedings of the 10th International Conference on Web Intelligence, Mining and Semantics (pp. 117-122).**

**DOI: https://doi.org/10.1145/3405962.3405965**

# Measuring Online Advertising Viewability and Analyzing its Variability Across Different Dimensions

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## ABSTRACT

Many of the current online business base completely their revenue models in earnings from online advertisement. A problematic fact is that according to Google more than half of display ads are not being seen. The International Advertising Bureau (IAB) has defined a viewable impression as an impression that at least 50% of its pixels are rendered in the viewport during at least one continuous second. Although there is agreement on this definition for measuring viewable impressions in the industry, there is no systematic methodologies on how it should be implemented or the trustworthiness of these implementations. In fact, the Media Rating Council (MRC) announced that there are inconsistencies across multiple reports attempting to measure this metric. For this reason, we select a subset of implementations to track viewable impressions and we perform a case study by implementing them in a webpage registered in the worldwide ad-network ExoClick in order to see their results on different dimensions. Our results show that the Intersection Observer API is the implementation that detects more viewable impressions and that there are significant viewability differences depending on the banner location on the website. Finally, we also propose an ensemble viewability method that proves to be able to detect a higher number of viewable impressions.

## CCS CONCEPTS

• **Human-centered computing** → **User studies**; • **Applied computing** → Online auctions; • **Information systems** → **Display advertising**; *Business intelligence.*

## KEYWORDS

Viewability, online advertising, web measurements, data mining

**ACM Reference Format:**
Marta Expósito-Ventura, José A. Ruipérez-Valiente, and Jordi Forné. 2020. Measuring Online Advertising Viewability and Analyzing its Variability Across Different Dimensions. In *The 10th International Conference on Web Intelligence, Mining and Semantics (WIMS 2020), June 30-July 3, 2020, Biarritz, France.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3405962.3405965


*WIMS 2020, June 30-July 3, 2020, Biarritz,France*

ACM ISBN 978-1-4503-7542-9/20/06…$15.00
https://doi.org/10.1145/3405962.3405965

## 1 INTRODUCTION

Advertisement has been used for many years to encourage consumers to acquire products, branding purposes and even to spread ideas. The new technological era has made advertisement to go through a re-imagination process moving from traditional media such as newspapers or billboards to digital medias like television, desktop computers and mobile phones. Nowadays, advertising has also trespassed the boundaries of targeting global populations to a more personalised and efficient approach that is specially tailored for the interests of each individual by using recommendation engines powered by the “big data” era [3]. Within this heterogeneous context we focus on digital display advertising (shortened as *ads* from now on), which can be found frequently in websites and apps in the form of banners and other various ad formats.

According to a report of the Internet Advertising Bureau (IAB) [10], the total expenses in online advertisement in the US during 2018 were 107 billion dollars, which represent a 21.8% more than in 2017. Many of the current online businesses and portals base completely their revenue models in earnings from online advertisement, allowing the end-user to have access to high quality contents or services free of charge [5]. However, recent studies [19] have found that more than half of the ads are not actually being seen, despite advertisers are still paying for them. The reasons behind these results are diverse, for example locating ads in a position of the webpage that consumers are unlikely to scroll to, the necessity of specific plugins to display ads or the use of ad blocker software, among others [6]. This has motivated stakeholders to start measuring viewable impressions, a new metric which the IAB[9] has defined as an impression that satisfies a percentage of pixels and time requirements within the viewport. In plain words, this metric attempts to measure which impressions could have been consciously seen by the user. However, since there is not consistency across results reported by different accredited measures when measuring viewable impressions, the MRC released a summary [16] saying that they do not encourage stakeholders to start using them for monetization purposes yet.

For this reason, this study aims to shed some light on the behaviour of the implementations that have been reported to be capable of measuring viewable impressions in the literature and the web. For this purpose, we test these implementations in a registered website in ExoClick’s ad network [1] and we analyze their viewability results across different dimensions. More specifically, the main objectives of this work are:

[1] https://www.exoclick.com

- To implement the methods reported in the literature and the web that allow us to comply with IAB measurement guidelines in a website with three banners.
- To analize the viewability results obtained presenting the following results:
  - Overview of the results by banner and implementation method.
  - Cross-sectional analysis based on different variables.
  - Inter-agreement between the methods.

The rest of the paper is organized as follows: in Section 2, we expose the state of the art of viewability in online advertising. In Section 3, we choose a set of IAB compliant viewability methods, we implement them, and test them in a website through an experimental study. In Section 4 we conduct analysis of the data collected and, finally, we present the conclusions and future work directions in Section 5.

## 2 RELATED WORK

Given the volume of resources spent daily on online advertising it is very important for all stakeholders to be able to measure the performance and effectiveness of ads. This is a challenging task since the perception of ads is related to various different factors such as user navigation behaviour (if the user is browsing aimlessly or not) [17] or the content of the webpage itself [7]. Although there is no standard measure for ad effectiveness, click-through rate (CTR) has been widely used to measure user interest on a product [4] but, as "IAB best practices for conducting online ad effectiveness" research pointed out [8], that metric is not longer recommended as a measure of ad effectiveness. This is due to the fact that average CTR value has been decreasing from 2-4% in 1998 to below 1% in 2004 [11]. One possible explanation to this decrease is that users have too much information online and they do not fully focus on what they are reading or watching [12]. Another explanation is the "banner blindness phenomenon" [2] where users decide to ignore page elements that resemble banners while reading a webpage due to the negative consumer responsiveness to them.

Besides user's interest in ads, another problem is that only half of the impressions displayed are actually viewable impressions [6, 19]. In 2014, the IAB defined a viewable impression as an ad impression contained in the viewable space of the browser window, on an in-focus browser tab that fulfils a pre-established criteria such as a minimum percent of ad pixels and time that an ad is visible within the viewable space of the browser (post ad render) [9]. Moreover, strong interactions with an ad (e.g., a click) are considered as viewable impressions as well. Since advertisers are interested in promoting and achieving conversions through ads, it is important for them to know if these ads became at least viewable to their potential clients. With this idea in mind, a new pricing model was proposed in [13] based on the number of viewable impressions, so that advertisers would be billed just for those ads that had the chance to be on the viewport of the user. This pricing model greatly differs from other traditional ones such as cost per mille (CPM), which refers to the price paid for every 1000 served impressions. However the MRC released a summary [16] saying that although viewability measure is a strong step forward for the online advertising community, it still needs to evolve to reach a good consensus across results reported by different advertisers, agencies and publishers. In fact, it is very important to have commonly defined metrics for consistency in reporting and analysis [1] since, without that, it is very difficult to have a baseline under which advertisers and publishers make business with a common understanding. For this reason, in this work we test different implementations to track viewable impressions in order to compare their results in different banner locations and in different browsers, operating systems and devices types.

## 3 METHODS

In this section we explain the setup of our experiment. First, we present the viewability categories found in the academic and practitioner literature. Afterwards, we continue by detailing the experimental and website design and as well as the data collection.

### 3.1 Viewability Methods

We have grouped the existing viewability implementations that we found in the literature and the web in three main categories:

(1) **Geometric.** This first category is based on the geometric properties of the ad relative to another element of the site [6].
(2) **Browser optimization.** It relies on the fact that some browsers save resources when certain elements are not on the screen, this feature enables the browsers' frame rate in order to know if the ad is being rendered in the viewport or not.
(3) **Strong interactions.** The third category is based on strong interactions with the ad, since if there is an interaction with it, that would imply that the user was able to see the ad [9].

One of our goals is to implement a viewability measure that fully complies with the IAB standard to measure viewable impressions. Therefore, we decide not to use browser optimisation implementations in this case study since these methods do not allow to measure the percentage of rendered pixels. Therefore, the final viewability implementations that we test are:

- Relative position (Geometric). This implementation utilises *element.getBoundingClientRect* JavaScript function to get the smallest rectangle that contains an element with its dimension properties in pixels. By using these coordinates we can estimate the relative position of the element with respect to the window's viewport.
- Intersection Observer (Geometric). The World Wide Web Consortium (W3C) has developed an API called "Intersection observer" [18] that asynchronously observes changes in the intersection of a targeted element with another element or with the document's viewport.
- Mouseover on an ad during at least one continuous second (Strong Interaction). The detection of this event can be obtained directly using the HTML *onmouseover* DOM event.
- Click on an ad (Strong Interaction). Clicks can also be obtained using the HTML *onclick* DOM event.

### 3.2 Experimental Design

For the purposes of the experiment, we select a site registered in ExoClick's network which has world wide traffic from different devices, browsers and operating systems and we perform a cross-sectional analysis by each one of the implemented methods and banners. The design of such site is represented in Figure 1 and it contains three banner ads of 300x250 pixels (the most widely used ad-format size in the web). The first banner is located in the left-top corner, and an user would always be exposed to it when visiting the site. The second banner is located a bit below needing some scrolling down to be viewable in any device. Finally, the last one is in the bottom of the site and it requires the user to scroll down through the entire site to be visible.

## 3.3 Data Collection

After one day of traffic, we have around a hundred thousand visits in our site. In order to filter out noise from this traffic, we remove those visits that are using adblock software, web crawlers, hosting proxies or users that do not support JavaScript code. The output is a broad variety of traffic that we can further analyse to know the results of our viewability implementations in each environment. By analyzing the final dataset, we see that most of the traffic comes from Asia followed by Europe, America and Africa. Moreover, the biggest percentage of impressions is from mobile devices, then desktop, and a little percentage from tablets and smart TV. The most popular operating systems have been Android, followed by Windows, iOS and lastly Linux. Finally, Chrome is the browser with more traffic, followed by Firefox, Safari and Internet Explorer.

**Table 1: Percentage of viewable impressions by banner**

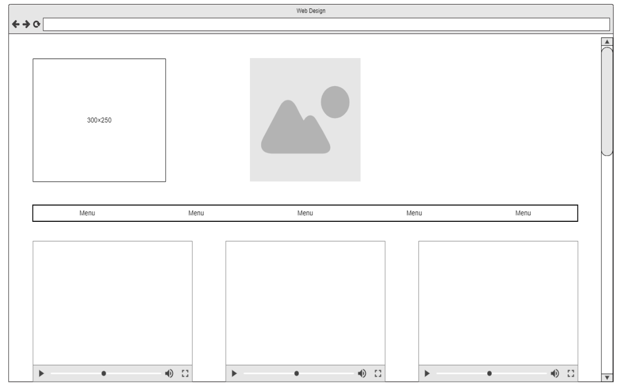
| **Implementations** | Banner 1 | Banner 2 | Banner 3 |
|---|---|---|---|
| Relative Position | 36.63% | 12.67% | 9.97% |
| Intersection Observer | 41.04% | 24.07% | 6.71% |
| Mouseover | 5.90% | 3.99% | 1.72% |
| Clicks | 4.42% | 1.10% | 1.01% |
| **Combined** | **56.47%** | **30.07%** | **14.14%** |

# 4 RESULTS AND DISCUSSION

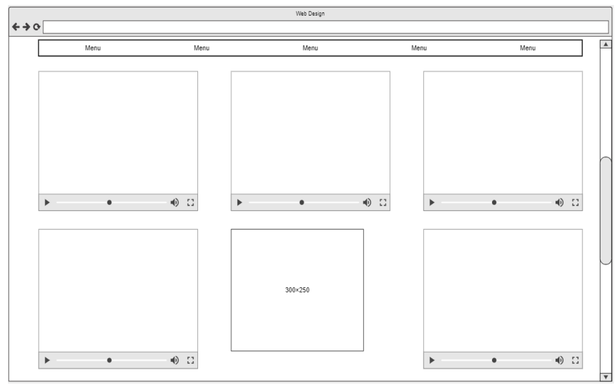
In this section, first we analyze the results obtained by each viewability implementation and banner, and we evaluate the possibility of ensembling all methods together to achieve better detection levels (Subsection 4.1). Also, we compare each method under different cross-sectional variable including the browser, OS and device (Subsection 4.2). Finally, we compute the inter-agreement values between the implementations in order to better understand their relationships (Subsection 4.3).

## 4.1 General Results

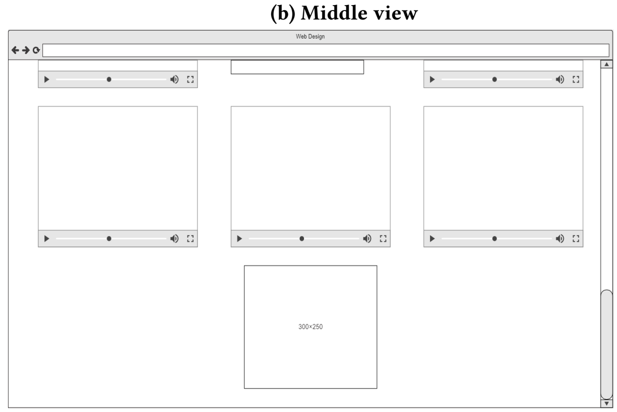
Table 1 presents the results regarding the percentage of impressions that were viewable by each implementation and banner. We also implement an ensemble method by combining results of all implementations together (i.e., the output would be an `OR` operation of the positive detection of all implementations); if we do so, in banner 1 we would be measuring 56.47% of the served impressions as viewable impressions. This value is very similar to the one reported by a Meetrics report [15] in 2019. If we assume that these measures do not have false positives and that banner 1 should have a high




**(a) Top view**




**(b) Middle view**




**(c) Bottom view**

**Figure 1: Design of the selected webpage. There are three banners, one in the top left of the front view (a), the second one in the middle view with minimal scrolling required from the user (b) and the last one at the bottom of the site (c) with a long scrolling from the user required.**

percentage of views because its position in the site (everytime that the user loads the site the banner 1 should be viewable), that means that there are still a 43.53% that are not viewable according to these implementations. This might be due to several reasons, such as (1) the user closing the site before the time requirement defined by IAB is met, (2) because the implementation was not able to track it due to technical issues (e.g., browser version, user not enabling JavaScript code, etc.) or (3) because the ad was, in fact, not viewable. In order to discard the first hypothesis, future work can aim to measure the actual time that each visit spends on the site. For the second hypothesis, a future implementation could periodically log the percentage of pixels in the viewport for each ad, and not just when it is above the 50%, as this can help to verify that the technical implementation is working correctly.

Nevertheless, these results suggest that the Intersection Observer API is the implementation that detects a higher percentage of viewable impressions when compared to the rest of implementations. These percentages make sense since the natural funnel of viewability should be first the ad being served to the site, then appearing viewable to the user, afterwards the user moving the mouse over the ad and finally clicking in the ad. The recall of actions decreases as the funnel goes onward, but at the same time the certainty of that ad actually being consciously viewed by the user also increases.

Moreover, it is interesting to note out how the percentage of viewable impressions decreases with the position of the banner. If we compare banner 2 with banner 1, we see that by locating the ad in the middle of the site and therefore, a bit hidden from the first view when the user opens the site, the amount of views detected decrease to more than half. For banner 3, which is at the bottom of the site, it also decreases almost to a third with respect to banner 2.

## 4.2 Cross-sectional Results

In order to understand when these implementations are not able to measure viewable impressions and to better understand the 43% that remain without being detected, we focus on banner 1 since, as mentioned before, it should have a high percentage of viewable impressions. We examine the results reported by each implementation with respect the average value of detected viewable impressions by each cross-sectional variables. For example, in Figure 2 we see that Intersection Observer is the implementation with higher viewable impression detection among all devices but smart TV, where Relative Position has more viewable impressions. In Figure 3, we see that in all browsers, the Intersection Observer detects the highest percentage of viewable impressions followed by the Relative Position, but note the small difference with respect the average for Firefox and Internet Explorer, where all the implementations are very close to their average. This is unusual since there should be more probabilities to have geometrical viewable impressions than strong interactions due to the natural funnel of viewability discussed earlier. Lastly, in Figure 4, we also see that for Linux and iOS all implementations are very close to the average of viewable impressions and the rest of operating systems show a more natural distribution respect the viewability funnel.

## 4.3 Inter-agreement Results

In the three figures we see that in general the Intersection Observer API detects more viewable impressions than other implementations. However, we also see that by combining all the implementations together it is possible to detect more percentage of viewable impressions than by just taking one into consideration. We can understand better the relationship between the different methods by computing

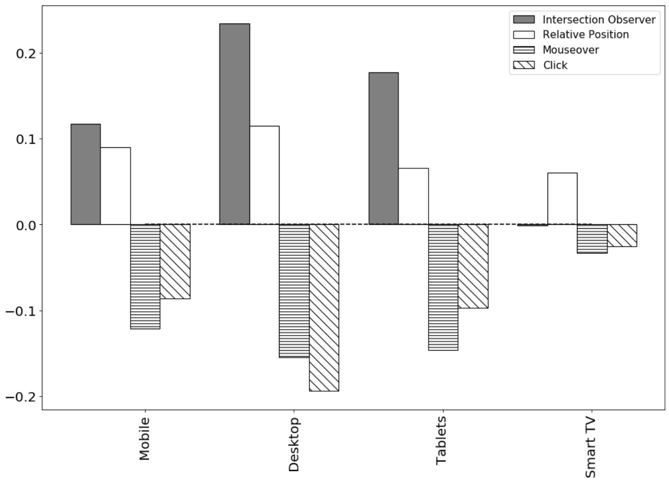



**Figure 2: Comparison of implementation by devices respect the average value of each device.**

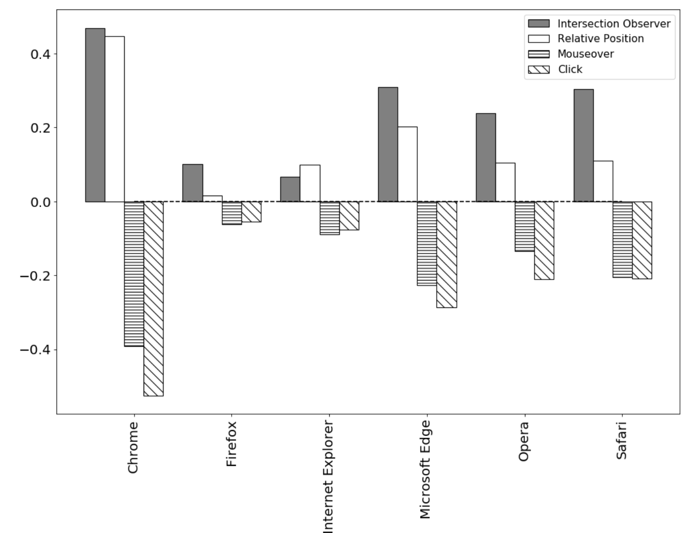



**Figure 3: Comparison of implementation by browsers respect the average value of each dimension.**

their level of inter-agreement. For this purpose, we apply the Cohen's Kappa score [14]. This score is a statistic value that measures the agreement between two categorical items taking into account also the hypothetical probability of agreement occurring by chance. If two metrics are in complete agreement the score should be 1, and if there is no agreement at all, the score should be 0. Results are displayed in Figure 5 and we see that geometric methods are the one with higher ratio of agreement, with a value of 0.5. Given the overall results of inter-agreement, we conclude that all methods here are contributing and have an important role to achieve higher results when detecting viewable impressions.

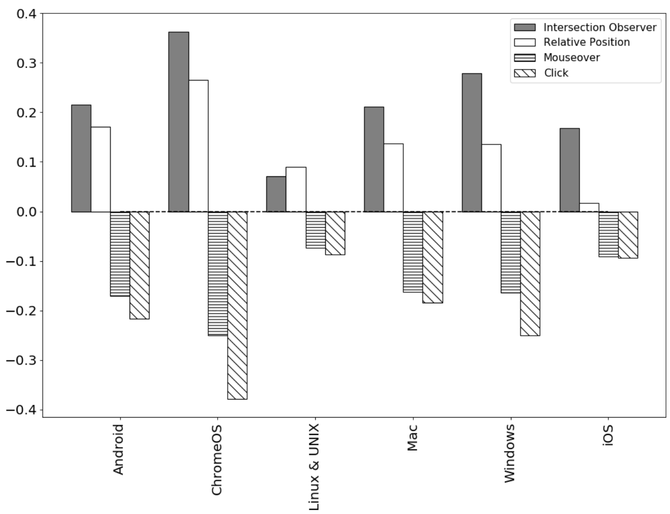



**Figure 4: Comparison of implementation by operating system respect the average value of each dimension.**

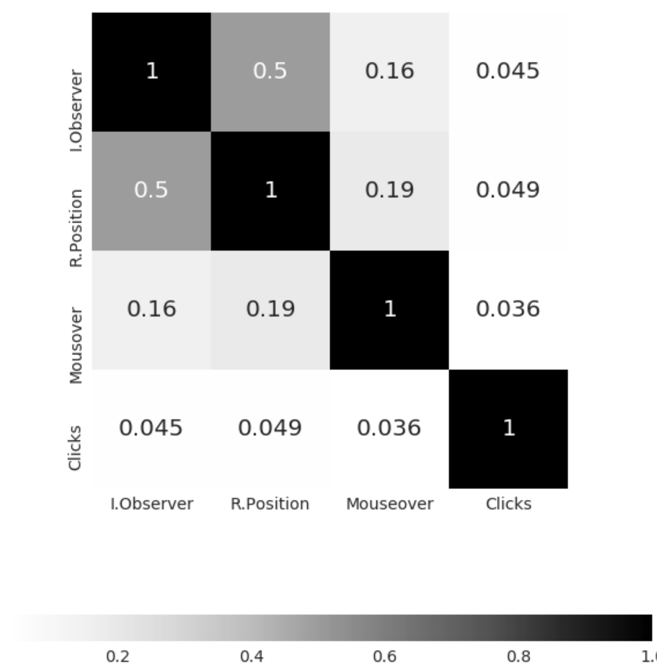



**Figure 5: Cohen's Kappa score between methods.**

## 5 CONCLUSIONS AND FUTURE WORK

In this paper we perform to the best of our knowledge the first viewability measurement comparison of reported viewability implementations in the literature and in the ad industry that comply with the requirements defined by the IAB. Specifically, we analyze their effectiveness applying them in a registered website of ExoClick ad-network with world wide traffic. From such analysis we report the following results:

- According to our results, Intersection Observer API is the implementation with higher detection of viewable impressions, followed by Relative Position.
- The difference in percentage of viewable impressions between ads is definitely influenced by their relative position in the site, being the banner 1 the ad with more viewable impressions, followed by banner 2 with less than the half of banner 1, and lastly banner 3 with half of viewable impressions than banner 2, which make sense since it is in the bottom of the site and there are less chances that the users scroll down there.
- Current viewability implementations are still far from being able to track all viewable impressions in all scenarios. We see that, by combining these implementations together it is possible to reach a higher value of positive detection, concretely a 24% more of detection.

Although the experiment that we have conducted is still preliminary, we hope this can motivate more stakeholders involved in the online advertising ecosystem to work towards the standardisation of viewability metrics in the ad industry, as these can have a very important role in their financial stability, policy guidelines and revenue models, that can then have a direct influence on the quality of the experience of Internet users. The main limitation of our work is that we have no ground truth regarding if an ad was in fact viewable or not by the user. While this is a hard-to-get ground truth, future work can develop case studies using humans to annotate which impressions they saw in order to detect false positives and negatives in the technical implementations. Future work should also collect richer data samples, implement broader case studies across multiple sites or the development of more robust methods that can work well across the diversity of the World Wide Web. Additionally, we should also analyze how these measures and findings translate to other ad formats, such as in-video ads or native ads, in order to find which viewability patterns are universal vs. those that are format-dependent. Finally, future research should also aim to study the intersection of human attention and cognition theories with the aesthetic features of the ads, as this can hold promising new grounds towards understanding viewability.

## 6 ACKNOWLEDGMENTS

This work was possible thanks to the support of "Plan de Doctorados Industriales de la Secretaría de Universidades e Investigación del Departamento de Empresa y Conocimiento de la Generalitat de Catalunya" and the Spanish Ministry of Economy and Competitiveness through the Juan de la Cierva Formación program (FJCI-2017-34926). We also want to thank ExoClick for their support in conducting this research.

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