Assessing Ad Attention through Clustering Viewport Trajectories

Lennard Lukas Schmidt
Google Inc.

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Completed Research Paper

Lennard L. Schmidt
HHL Leipzig Graduate School of Management
Jahnallee 59, 04109 Leipzig
lennard.schmidt@hhl.de

Erik Maier
HHL Leipzig Graduate School of Management
Jahnallee 59, 04109 Leipzig
erik.maier@hhl.de

Abstract

Advertisers have to pay publishers for "viewable" ads, irrespective of whether the users paid active attention. In this paper, we suggest that a granular analysis of users' viewing patterns can help us to progress beyond mere "viewability" and toward actual differentiation of whether a user has paid attention to an ad or not. To this end, we use individual viewport trajectories, which measures the sequence of locations and times an object (e.g., an ad) is visible on the display of a device (desktop or mobile). To validate our model and benchmark it against the extant models, such as the "viewability" policy (50% threshold) model, we use data from an eye-tracking experiment. Findings confirm the improved model fit, highlight distinct viewing patterns in the data, and inform information processing on mobile phones. Consequently, implications are relevant to publishers, advertisers, and consumer researchers.

Keywords: ad attention, viewport tracking, dynamic time warping

Introduction

Digitalization of more areas of our daily lives promises to unveil many more forms of consumer behavior. The keyword "big data" summarizes the hope of many practitioners and researchers to be able to use more extensive data sets on a pervasive set of phenomena, which can be analyzed with the help of advanced analytical procedures to understand consumers more fully and to make better decisions (Agarwal and Dhar 2014; Grover et al. 2020; McAfee and Brynjolfsson 2012). This beacon of hope shines particularly bright for many marketers, which aspire "for better and more detailed causal explanations [of consumer behavior] as well as recommendations for optimal actions at higher levels of specificity and granularity" (Wedel and Kannan 2016, p. 109). Yet, to date, many areas of digital consumer behavior remain inexplicable (Fulgoni 2016; Kannan and Li 2017) and marketing practice often remains limited to simple heuristics—simplifications that cost companies money, for instance in digital display advertising (Hobbs 2016). This research explores how to improve one area which suffers from a need for simplification: the measurement of attention to mobile display ads. Through making use of granular and readily available (mobile viewport) data and advanced analytics (dynamic time warping), we hope to contribute as information systems research through combining technology and data to solve a relevant (marketing) business question (Agarwal and Dhar 2014).

Digital advertising is a highly relevant and growing industry: The digital advertising volume is continuously increasing, and especially mobile marketing is growing rapidly with more than 20% per annum, reaching almost 90 billion USD in 2019 in the United States alone – roughly 60% of which are so-called display ads (i.e., banners, rich media or videos; eMarketer 2020). Through display ads, advertisers want to direct consumers' *attention* to their products or services. Yet, as ad attention (i.e., the active viewing of an ad) cannot be measured at scale directly, the industry-standard—upon which also payment rests—relies on a simplification rule: the so-called "viewability". An ad is labeled as "viewable" if 50% of it was visible on a user's display for more than a second (Media Rating Council 2014). Advertisers have to pay publishers for "viewable" ads (Google 2020), irrespective of whether the users paid active attention. However, using this "viewability" as a measure of attention is, following industry experts, "ludicrous", as only 9% of the "viewable" ads are actively viewed (Hobbs 2016). In reality, phenomena such as "banner blindness" make users avoid paying attention to viewable ads (Sun et al. 2013).

We suggest that a more granular analysis of users' viewing patterns can help us to progress beyond mere "viewability" to an actual differentiation of whether a user has paid attention to an ad or not. In this, we use individual viewport trajectories, which measures the location and time with which an object (e.g., an ad) is visible on the display of a device (desktop or mobile; Grusky et al. 2017). This results in a sequence of observations as website elements (here: ads) move through the viewport. Based on these viewport trajectories (or paths: Hui et al. 2009), one should be able to differentiate active viewing (i.e., attention) from inattentively scrolling over an ad, by analyzing the pattern and speed with which an ad moves through a user's viewport. Two simple examples illustrate this: (1) an ad might be labeled "viewable" for a user that does not actively view it. If a user focuses on content below or above the ad while continuously scrolling over the focus content, a constant but quick progression of the ad through the viewport should result, in which the ad is likely to be "viewable" for more than a second (and, hence, costs the advertiser money), without having received focused attention. In contrast, (2) if a user actively views a "viewable" ad, we would expect that the ad receives higher overall viewport time and shows peaks in viewport time at some position of the viewport (i.e., where the viewer paid active attention). Thus, viewer attention to an ad should result in higher overall viewport time and specific, potentially peaked, viewport trajectories.

A viewport trajectory-based assessment may explain ad attention better than mere "viewability": There is substantial behavioral variance in the way consumers interact with ads (Rosbergen et al. 1997), for instance as some consumers aim to avoid seeing ads while others do not (Hervet et al. 2011; Teixeira et al. 2012). Ignoring ads that are viewable in the display is common among many consumers ("banner blindness": Sun et al. 2013), which necessitates aproaches for estimating ad attention that account for heterogeneity in the way ads are viewed. Viewport trajectories allow capitalizing on this heterogeneity through clustering, as they offer more granular data than "viewability", which aggregates information from the trajectories to a dichotomy (viewed for more than 1 second vs. not) and might, therefore, yield misleading results (Rosbergen et al. 1997). Further, trajectories capture how consumers interact with the ads in their environment, making dynamic choices (Hui et al. 2009).

We build upon extant research that established viewport tracking as a method for studying active information retrieval (e.g., Grusky et al. 2017; Lagun et al. 2014). We account for consumer heterogeneity in viewport data, by employing a hierarchical sequence clustering with dynamic time warping (Berndt and Clifford 1994) to identify clusters of trajectories across the viewport data of heterogeneous viewers. This approach makes use of the viewport data in its full granularity and is agnostic to the position of an ad, which is relevant in an advertising context because the position of display ads strongly varies (in contrast to search rankings: Resnick and Albert 2014). We illustrate our approach for mobile phone screens as mobile advertising is increasingly relevant and ideally suited for using viewport data because the small screens that the viewability of an ad only varies in one dimension (i.e., either scrolling or swiping through content; Lagun and Lalmas 2016).

Using data on actual ad attention obtained from an eye-tracking study, we compare different viewport models (uniform time-based, hierarchical sequence clustering) with the established policy model (i.e., the 50% rule). We find that hierarchical sequence clustering of viewport trajectories identifies actual ad attention substantially better than uniform viewport models or the established policy model. Additionally, clusters of viewport trajectories also best explain downstream consequences, such as ad recall (Batra and Keller 2016).

Our findings extend extant research by (1) contributing to the managerially highly relevant debate of how to measure ad attention (e.g., Degtev 2019; Hobbs 2016; Neff 2018), introducing an approach to assess ad attention that could be implemented by publishers in the field. We benchmark this approach against policy heuristics (50% "viewability" threshold) and a uniform viewport sequence. Additionally, we (2) offer empirical evidence how consumers view ads (between exploration and focused attention), a topic which receives substantial research attention beyond the advertising context (Otero-Millan et al. 2013), and is of special relevance for information processing on mobile phones (Grewal et al. 2018). We (3) also contribute to the debate about incidental ad exposure (Shapiro 1999), highlighting that differentiating ad viewing patterns (assessed through viewport trajectories) helps to understand the effect advertising on downstream measures, such as recall. Finally, we (4) extend the applicability of viewport tracking beyond the context of directed information retrieval (search overviews or newspapers). In this, we methodologically extend existing approaches to account for user heterogeneity in the interaction with website elements (here: ads) in a way that does not require researchers to pre-specify the position of website elements.

Background

Ad Attention, its Behavioral Variance, and Consequences

Viewing ads is not an active information retrieval process, but rather a side product of another primary task (as, e.g., reading a newspaper: Shapiro 1999). Theoretically, dual-process theories (e.g., the heuristic-systematic processing model: Chaiken 1980) highlight that, due to an overload of information from relevant content and ads, viewable ads are often automatically ignored (Cho and Cheon 2004) and not processes systematically. This phenomenon is exacerbated in today's multi-screen environment (Duff and Segijn 2019). Thus, that an ad is viewable does not mean users paid attention to it (Lee and Ahn 2012). Therefore, research on ad attention is concerned with understanding user's drivers of consumers' decision to pay attention to an ad (Liu-Thompkins 2019), such as the frequency and duration of exposure (Schmidt and Eisend 2015) or how strongly an ad stands out (Baron et al. 2014; Pieters et al. 2002).

To understand ad attention more granularly, ad research is highly interested in understanding how and in which patterns consumers view ad content (e.g., Farace et al. 2020; MacInnis and Jaworski 1989). The most established distinction of viewing patterns in extant research is that between exploration, where consumers quickly skim through information and focused attention (Otero-Millan et al. 2013). Additionally, there is evidence that there are different modes of ad viewing (Sun et al. 2013). Rosberg (1997) finds that three patterns are common in the processing of ads: (a) scanning, (b) initial attention and (c) sustained attention, to which we add inattention to the ad, but (d) attention to an object above the ad – in which case a "viewability" classification might register attention. Fig. 1 develops illustrative viewport trajectories (i.e., movement patterns over the ad) for these patterns. A "viewability" assessment of attention would register all but the (a) screening pattern as viewable, while the ad in patterns (a) and (d) is unlikely to have received attention.

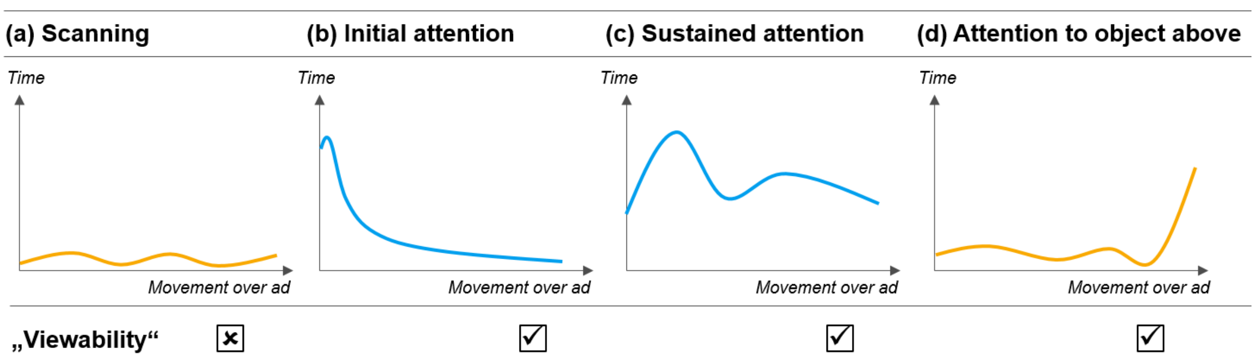

Figure 1: Illustrative viewport trajectories based on ad attention patterns suggested by Rosberg (1997)

We investigate ad viewing trajectories on mobile phones, both for a managerial and a methodological reason. Due to the growing managerial relevance of mobile ads (eMarketer 2020), understanding how ads are processes on mobile phones is particularly relevant (Goh et al. 2015; Grewal et al. 2016). However, to the best of our knowledge, no investigation has yet offered information on ad viewing patterns on mobile devices. Methodologically, due to the linear orientation of content on mobile websites along the vertical dimension (i.e., one content element after another from top to bottom of the page) viewing trajectories on mobile phones can be reduced to a single dimension and, consequently, offer an ideal testbed for clustering viewport trajectories. We, therefore, aim to investigate:

RQ1: Can users' viewing patterns of a website (measured through the device viewport) explain actual visual attention on mobile phones?

The effectiveness of online ads is of great interest to researchers and practitioners alike (Liu-Thompkins 2019; Tellis 2014). In this, it is not clear that only active ad attention will cause desired response (e.g., recall), as the debate about the effects of incidental ad exposure shows (Shapiro et al. 1997; Shapiro 1999; Yoo 2008). We, therefore, also investigate the downstream effects of different types of ad engagement. Heterogeneity in ad engagement arises from both an interpersonal and an inter-ad variance.

Interpersonal heterogeneity: Research on ad exposure indicates that consumers show a substantial variance in their interaction with websites in general (Buscher et al. 2010) and advertisements in particular (Grewal et al. 2016; Urban et al. 2014). Besides a general tendency to avoid engaging with ads, factors that vary interpersonally and inter-situationally drive ad avoidance (e.g., prior negative experience with ads, or how strongly an ad impedes my primary goal: Cho and Cheon 2004). As an extreme form, so-called "banner blindness" (i.e., the tendency to fully overlook display ads: Sun et al. 2013) varies between consumers (Hervet et al. 2011), but also less extreme forms, such as the decision to disengage with an ad, vary interpersonally (Teixeira et al. 2012). This should result in different behavioral responses, that is: scrolling, that manifest in different screen content, especially if the screen upon which an ad is viewed is small (such as a mobile phone screen). In line with this proposition, research on newspaper reading finds that variance in browsing behavior (Lagun and Lalmas 2016). Thus, we suggest that consumers have an overall tendency toward one pattern of ad attention.

Inter-ad heterogeneity: Additionally, also ads are viewed differently: some ads might catch a lot of attention (e.g., due to their content, design, or serial position: Wang et al. 2019) while others might be overlooked, as they blend more strongly into their context. Viewport trajectories should be able to capture also within-consumer heterogeneity.

The question remains, however, whether the clustering of different trajectory patterns offers sufficient information to explain ad awareness. We suggest that due to their greater granularity, pattern clusters identified from viewport trajectories are better able to explain ad attention than mere "viewability".

RQ2: Can viewing patterns of an ad explain ad awareness, as a downstream consequence of an advertisement?

Current Methods for Assessing Ad Attention

"Viewability" Policy Model: In practice, ad attention is assessed in two ways. For search ads (e.g., Google SEA), on the one hand, attention is measured through direct interaction with the object, by capturing what consumers have clicked upon (resulting in "costs per click": Asdemir et al. 2012). For display ads, on the other hand, attention cannot be measured through clicks, as display ads are not only developed to be clicked upon (in contrast to a paid link in a search engine ranking) but also serve an overall branding purpose (Ghose and Todri-Adamopoulos 2016). Commercial ad networks, therefore, use "viewability" as a proxy, implementing a policy that counts the exposure frequency with which an ad has been shown on users' displays, given that at least 50% of the ad's area is visible for more than one second (Google 2018; Media Rating Council 2014). This approach, which we refer to as "policy model" assumes that exposed ads are also viewed, resulting in several views which are then charged, ("cost per view"). In advertising research, this number of views is often used as independent variable (e.g., Braun and Moe 2013). The validity of this "viewability" count and the height of the minimum visibility level is, however, subject to a substantial debate in practice, as the threshold is rather arbitrary (Neff 2018) and views might have been generated by bots (Zhu et al. 2017).

Eye Tracking: An alternative means to assess ad attention, which is often employed in scientific research (e.g., Ahn et al. 2018), is eye-tracking, where attention is captured through a camera recording of a user's gaze time or as fixation time or count (Higgins et al. 2014). Eye-tracking, however, is often impractical in the field, as it is very resource-intensive (Grusky et al. 2017), despite a recent decline in the equipment costs (Wedel and Pieters 2008), because it requires a controlled environment and a great deal of time of the researcher to map the gaze time (commonly recorded at a frequency of 60Hz) to the tested material. Eye-tracking, therefore, has been limited to laboratory settings (e.g. Lee and Ahn 2012; Li et al. 2017). Because eye-tracking measures actual attention through fixations (Higgins et al. 2014), we will later employ eye-tracking as ground truth for the actual ad attention in our empirical study.

Extant research using viewport tracking

Viewport tracking might be an approach that helps to assess consumers' ad attention while accounting for consumer heterogeneity in ad viewing. Extant research has already employed data obtain from user viewports (see Table 1), so far, however, exclusively focused on active information retrieval, either of content pieces from news websites (Grusky et al. 2017; Lagun and Lalmas 2016), or the results of search engine rankings (Lagun et al. 2014; Lagun and Lalmas 2016). While most of the research offers a uniform assessment, which does not differentiate between different types of viewing patterns of a website, Lagun and Lalmas (2016) differentiate between different user groups. They establish that in active information retrieval processes, consumers differ in their progression over six different elements of a newspaper website (e.g., bottom, top, comments). Extant research partially compares viewport trajectories to the ground truth of actual viewing and fixation patterns obtained from an eye-tracking study (Lagun et al. 2014; Lagun et al. 2016), but focuses on gaze time only, while actual fixations are preferable in an advertising context (Hoffman and Subramaniam 1995).

Study	Viewing patterns		Comparison to ground truth	Focus	Context
	Uniform	Clustered			
Lagun et al. 2014	✓	–	✓ (gaze)	Information retrieval	Mobile search engine results
Lagun et al. 2016	✓	–	✓ (gaze)	Information retrieval	Mobile search engine results
Grusky et al. 2017	✓	–	–	Information retrieval	Desktop news website
Lagun and Lalmas 2016	✓	✓	–	Information retrieval	Desktop news website
Our research	✓	✓	✓(fixation)	Ad attention	Mobile news website

Table 1. Extant research using viewport tracking

Method

Viewport tracking

The viewport can be characterized as the "portion of the web page that is visible on the phone screen at a given point in time" (Lagun et al. 2014, p. 2). As the user interacts with the website (e.g., by scrolling the page), the viewport changes, and reveals previously covert parts of the website to the user. Tracking these changes to the viewport is also referred to as viewport logging (e.g., Lagun et al. 2016) and results in measures of viewport time, or the time that a part of the website stays visible to the user. Since a website is a composition of different content elements (e.g., ads, search results, news content), viewport time can be attributed to each of the objects that are visible in the viewport, potentially by taking into account the share of the website occupied by the element (or, in the policy model for assessing ad attention, a threshold of 50%). This tracking of different objects results in viewport trajectories or the duration with which an object is visible indexed by its movement over the screen. For our investigation, we do not track viewport events for the full webpage, but only for our focal object, the embedded advertisements, and record the vertical position (as the main dimension on which the viewport changes) and time that the element stayed at that position, which yields panel data for each advertisement by the position.

Fig. 2 offers an illustration of viewport tracking on a mobile phone. Panel (A) shows how content moves through the phone while scrolling. Panel (B) offers a heatmap based on our empirical data on which part of the screen viewers pay most attention, which we will interpret in the following section. Panel (C) highlights with the gaze plot of one viewer on how consumers view an ad: content moves onto the screen from bottom to top; therefore, exploration of an ad start at the bottom of the screen, and fixations happen at the top of the screen. This results in the illustrative viewport trajectory shown in Panel (D), which highlights that most attention is paid when the ad has moved into the top viewing region of the screen.

Viewport tracking can readily be implemented into various HTML applications (website, surveys, and experiments) using the JavaScript Intersection Observer API. Our implementation followed multiple steps: First, the program adds a so-called listener to each uniquely identifiable object on the webpage (e.g., a banner ad). Second, as soon as one (or more) of the observed object enters the viewport or changes its position within the viewport, the object-specific listener records the activity. Then a function logs the vertical position (in pixels from the top of the website) and the share of the element visible in the viewport (from .5 to 1), sets a timestamp, and compares it to previous timestamps for each position change. This process results in an array of tuples of positions and position-specific times (measured in milliseconds) and position-specific visibility shares for each observed element. The researcher can flexibly decide, which objects to assess (e.g., ads, products, text pieces).

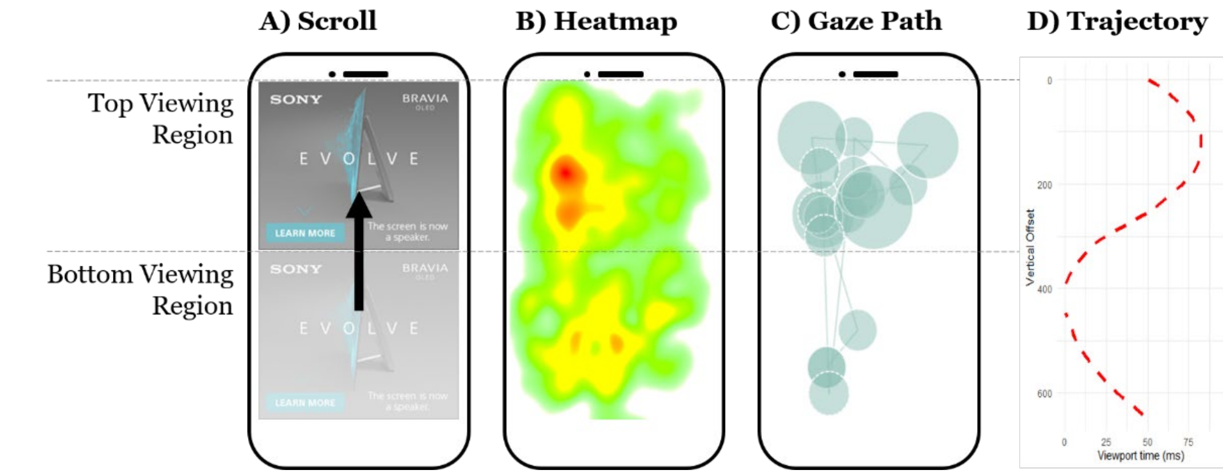

Figure 2. A) Content orientation and scrolling direction, B) heatmap of ad fixations (color is proportional to absolute duration averaged over all sessions: red = highest duration, green = lowest duration), C) gaze trail of ad fixations of one viewer (size of the circle proportional to duration of fixation in a single session) and D) simplified trajectory of viewport time over vertical offset of the screen

Formally, the viewport time for the vertical position j of the centroid (50% of height) of an advertisement e_i can simply be represented as the time t_{ij} that the centroid of advertisement e_i is located at position j. For instance, if the centroid of an advertisement would be located in the middle of an 800-pixel screen for 3 seconds with the full advertisement visible, our viewport logging would record the tuple $(400, 3000, 1)$.

Comparison to other Approaches

We will compare three different approaches for assessing user attention: (1) the "viewability" *advertising policy model* using the established 50% threshold, (2) the *uniform viewport time model* using an average of viewport time and (3) the *viewport trajectories model* using the full sequence of viewport observations (see Table 2 for an overview).

(1) Advertising policy model: In the traditional advertising policy model, each advertisement is labeled "viewable" and assumed to have received attention, if it meets two criteria (Google 2018; Media Rating Council 2014). First, the pixel requirement: Greater than or equal to 50% of the pixels in the advertisement need to be visible in the viewport. Second, the time requirement: The time the pixel requirement is met needs to be greater than or equal to one continuous second after the ad rendering. For this assessment, the viewport observations are transformed into a dichotomous variable, representing whether or not the policy defaults to true. Formally, for each advertisement e_i:

$$Policy(e_i) = \begin{cases} 1 \; when \; \geq \; 50\% \; of \; advertisement \; pixels \; in \; viewport \; for \; \geq \; 1 \; sec \; and \\ 0 \; else \end{cases}$$

(2) Uniform viewport time model: Following Lagun et al. (2014) in assuming a uniform distribution of user attention across the viewport, the share of the advertisement visible at every measurement should be the only determinant for the length of fixation. In this model, the viewport time for element e_i consequently is the sum of viewport times over all vertical positions J weighted by the share s_{ij} of the advertisement visible to the user. This approach, thus, disregards (a) the pattern with which an ad is viewed by each viewer, and (b) does not account for viewer heterogeneity. Formally:

$$ViewportTime(e_i) = \sum_{j=1}^{J} t_{ij} * s_{ij} .$$

	Models			Ground Truth
	"Viewability" policy	**Uniform viewport time**	**Viewport trajectories**	**Fixation time**
Approach	Ad marked as seen if (a) > 50% displayed for (b) > 1 second	Total time of an ad > 50% in the viewport	Hierarchical sequence clustering	Total time an ad has been fixated
Database	Cross-section of ad presence (across viewers)	Cross-section of viewport time for each ad	Sequence of ad position in viewer viewport	Cross-section of fixation time for each ad
Generated data	Binary	Metric	Clusters of trajectories (based on dynamic time warping)	Metric
Utilization	Benchmark of current business practice	Benchmark to practice in extant viewport research	Considered novel approach	Benchmark of ground truth (validation)

Table 2. Approaches to assessing ad attention

(3) Viewport trajectories model: User viewing patterns, however, may follow distributions that are more complex and non-parametric. In fact, the movement path of an advertisement in the viewport may be strongly linked to the amount of attention that a user is allocating to it. The fine-grained nature of the viewport observations (i.e., each element e_i recorded as a series of sequential observations, given their vertical position j $\{e_{i1}, e_{i2}, \ldots, e_{ij}\}$), allows us to test this idea using explorative techniques to identify common patterns or trajectories in the viewport data that may help to explain whether a viewer paid attention or not. Although multiple techniques are available (e.g., Hidden Markov Models [Lagun and Lalmas 2016]), we use sequence clustering to identify the most common trajectories, because the method does not operate on linear alignment of the sequence (Gales and Young 2008), and is, therefore, able to handle non-linear alignment between the sequences (Morel et al. 2018), thus accounting for heterogeneity in viewer response and changing ad position.

Dynamic time warping: The dynamic nature of the data requires different distance metrics compared to static cluster analysis to quantify the dissimilarity of the sequential observations. A variety of distance measures for sequential series exist, such as the shape based distance (Paparrizos and Gravano 2015) or the global alignment kernel (Cuturi 2011). To find the optimal clustering solution, we test different configurations of both hierarchical and partitional sequence clustering algorithms with a variable number of outcome clusters using R package "dtwclust" (Sardá-Espinosa 2019). The most homogenous solution (based on a combination of indices such as the Silhouette index, Davies-Bouldin index, or Calinski-Harabasz index) was achieved using hierarchical clustering with McQuitty's linkage (McQuitty 1957) and five output clusters. We used dynamic time warping as distance metric, which aims at finding the optimal warping path between two sequences (Berndt and Clifford 1994). Cluster prototypes were computed using partition around medoid algorithm, which reduces the average distance to all other sequences in the cluster. In information systems, dynamic time warping has been used to study learning effects in virtual reality applications (Huey-Min Sun 2016) or to identify false-positive in data collected from Radio Frequency Identification (Keller et al. 2014).

Empirical investigation

Design

Our empirical design is closely oriented at replicating existing designs from eye-tracking research on advertisements (e.g., Lee and Ahn 2012; Simola et al. 2011), but applied to mobile phones. We use eye-tracking of consumers' viewing patterns on their mobile phones as a measure of ground truth, to which ads consumer paid attention. We investigate whether different viewport-based proxies for attention (e.g., the advertising policy model) explain actual visual attention.

Upon arrival at the lab, participants (n = 37) were instructed that they were participating in a usability study of various websites in exchange for monetary compensation. They were subsequently fitted with a Tobii Pro Glasses 2 (all participants had a normal or corrected-to-normal vision) before a calibration procedure was performed and participants were handed a mobile phone (Samsung Galaxy S6; OS: Android; Browser: Google Chrome). Participants were instructed to hold the mobile phone vertically at a viewing distance of about 50cm. They browsed four news articles according to their interest and pace "as they would do at home or on the move" (i.e., self-paced). The presented articles were randomly sampled from a larger set of seven articles on different topics (e.g., music, technology, food; mean number of words: 709). Depending on its length, each article included at least two mobile display ads (200 × 250px) that were randomly sampled from a larger set of 25 different branded ads for different products (e.g., sports shoes, airlines, and cloud services) from 5 industries (food, lifestyle, service, sports, and tech), which were placed between paragraphs of approximately 275 words. Thus, consumers saw at least eight different ads throughout the experiment. After participants finished browsing the websites and reading the articles, they were asked to indicate unaided (open text input for recalled features [e.g., brand]) and aided ad recall for all of the 25 branded display ads (multiple-choice from all ads; Kuisma et al. 2010).

During browsing, we observed ads and their corresponding viewport metrics using the Intersection Observer API, which was embedded in the website's JavaScript. We recorded eye-tracking data throughout the whole experiment and post-processed it using Tobii Pro Lab (i.e., fixations were calculated using Tobii I-VT Fixation filter [Olsen 2012] and were subsequently mapped to the advertisements). Using fixations as ground truth variable differs from extant research, which utilized users general gaze (Lagun et al. 2014; Lagun et al. 2016), but aligns with ad research which extensively uses fixations as a measure of attention (Kuisma et al. 2010; Lee and Ahn 2012; Wedel and Pieters 2000). As fixations are a richer indicator for attentional processing as compared to gaze time (which also includes saccades, e.g., Hoffman and Subramaniam 1995; Sperling and Weichselgartner 1995), choosing this dependent variable will increase the external validity of our findings.

To show the different efforts involved in the post-processing: for viewport tracking, the JavaScript library generated a large data file that was almost completely ready for analysis, while the eye-tracking post-processing requiring roughly five working days of labor. Post-processed raw data from both methods were joined into a single data panel with measures per participant.

Results

Ad exploration and fixation from the eye-tracking data: We first aim to explore descriptively how users view ads on mobile phones. First indication for the importance of investigating ad trajectories in the viewport can be found when looking at the heatmap from the eye-tracking experiment (see Figure 2, Panel A). A clear pattern emerges, as fixations and their duration seem to be spatially correlated and primarily clustered in two different areas of the mobile phone screen. The first area of interest, which attracts a large number of fixations, is located in the bottom third of the screen. This area coincides with the location where, in linear scrolling, the display ads will first appear. The second area of interest, which attracts even more and longer fixations, is located in the top third of the screen. This area has been identified by extant literature to attract the most attention in search tasks (Lagun et al. 2016).

Looking at the sequential dimension of these fixations (Figure 2, Panel C), we can confirm this two-step process in ad processing. Upon appearance in the viewport, users seem to gather information (i.e., exploration) using few, short fixations (or saccades) to inform the decision of whether an ad will be subject to further processing. If so, the user will scroll the ad upwards in the screen in a second step and extract additional information from the image using many, long fixations. If the user decides that the ad will not be processed, it will be scrolled out-of-view. This evidence mirrors the distinction between visual exploration (i.e., short fixations and saccades) and fixation (i.e., longer fixations; Yarbus 1967). We can also show that higher fixation time is associated with a higher likelihood to recall an ad (see Figure 3A: $p < .001$, Figure 3), while saccade time, which indicates exploration, does not explain recall (Figure 3B: $p = .63$).

From this initial analysis, we can conclude that 1) it is likely that users will decide on whether to investigate an ad in-depth at the time it is initially displayed on-screen and 2) the time an ad will be investigated in the top third of the screen will be highly predictive for whether it has been processed in-depth and will consequently be recalled. This is initial evidence that ad trajectories across the mobile phone screen may be indicative of the user's attention and recall.

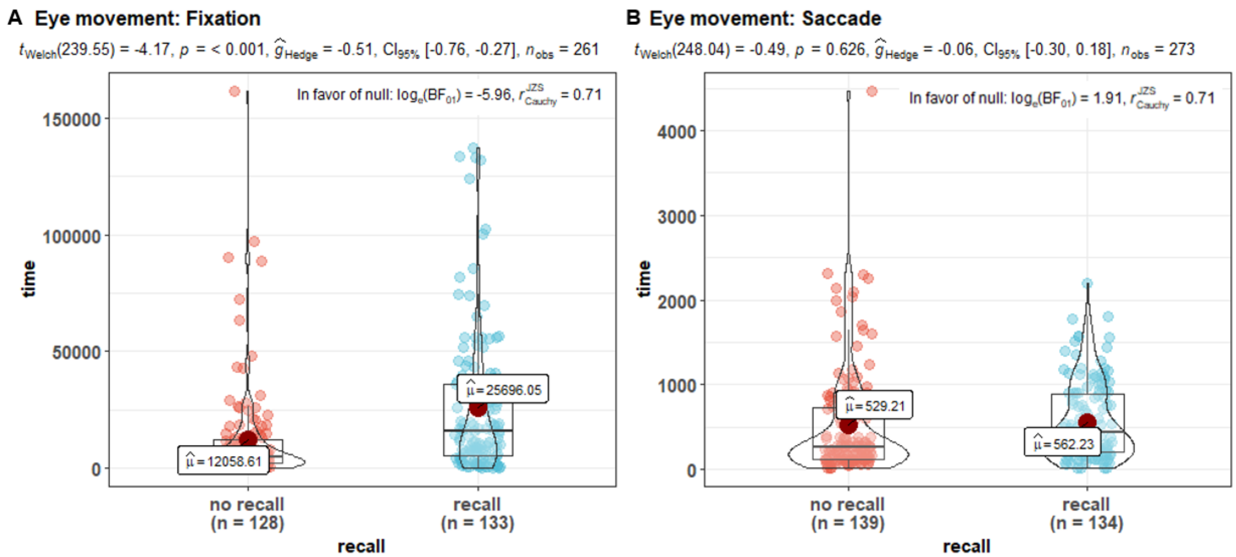

Figure 3. Distribution of eye-tracking fixation and saccade times for ads that are recalled vs. non-recalled. T-test summary statistics given in labels.

Clustering viewport trajectories: To disentangle the dynamics of advertisements across the screen, we visually investigate different patterns in the recorded viewport data using the sequence-clustering algorithm outlined in the method section and used in the model comparison. The unique clusters are illustrated in Figure 4 (Cluster E is not plotted, due to its extreme scale). Additionally, we plot the uniform distribution across all participants (Figure 4, grey broken line in all clusters), which aligns with our descriptive findings from the eye-tracking experiment (see Figure 2 and 3). We can see that the peak of the distribution is skewed to the left (i.e., the top of the screen). The distribution, however, also has a second, smaller peak at the rightmost side of the plot (i.e., bottom of the screen).

Visually, the viewport clusters in Fig. 4 are distinct in the trajectory that the ad takes across the screen and match established ad viewing patterns (Rosbergen et al. 1997 and Figure 1): Cluster A seems to be completely flat and indicates that the ad has only been "screened" and scrolled out-of-view immediately after its inset on the screen. In contrast, in cluster B, the ad received a lot of initial attention at the bottom of the page, but attention then drops at the top of the page (where the ad is usually fixated). This aligns with the "initial attention" pattern of viewing ads. Cluster C shows a peaked pattern, where the ad receives attention when already well into the viewport (at ~160 pixels) – this coincides with the screen region where users usually fixate ads. We, therefore, interpret this pattern as "attention". Finally, cluster D shows that viewers quickly scrolled over the ad at the bottom of the page, but that the ad moves more slowly over the screen the further it moves to the top of the page. We interpret this as a case where users actually paid attention to the object below the ad, which would explain why the viewport time steadily increases the more the ad moves out of the screen. Please note that the frequency of the clusters is independent of product type ($X^2(16, N = 333) = 14.604, p = .554$), content of the article ($X^2(24, N = 333) = 25.543, p = .337$) and the product itself ($X^2(96, N = 333) = 80.446, p = .873$).

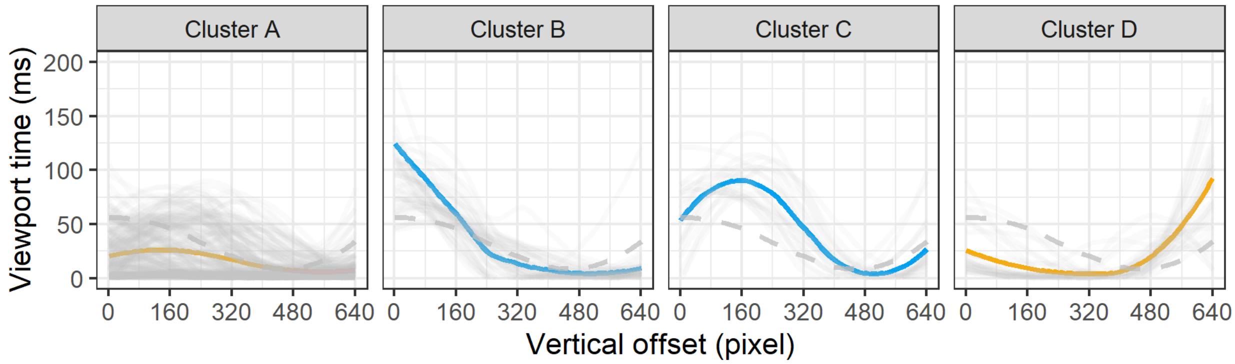

Figure 4. Distribution of viewport time across the screen for clusters A-D (and assigned individual trajectories) identified using dynamic time warping distance. Average distribution of viewport time across all observations in grey.

Explaining actual visual attention (RQ1): To investigate whether viewport trajectories explain actual visual attention (RQ1), measured through eye-tracking fixations as our ground truth, we fit multiple linear models. In this, we compare the (1) "viewability" policy model with (2) the uniform (i.e., non-cluster) viewport model and the (3) clustered viewport model. Table 3 summarizes the model coefficients and corresponding indicators for goodness-of-fit (i.e., R^2, adjusted R^2, AIC, and BIC). We find that the (1) policy model does not explain fixation time. By contrast, the (2) uniform viewport time model helps to explain about 1% ($Adj. R^2 = 0.010; AIC = 7701{,}013$) of the variance in the dependent variable. The viewport trajectories model (3), which includes a variable that indicated cluster assignment, finally, outperforms both the policy model and the uniform viewport time model by explaining an addition 3.9% $Adj. R^2 = 0.049$; AIC = 7690,845) of the variance in fixation time (. Coefficients indicate that cluster C $b = 22{,}248.140, p < 0.001$), and D ($b = 11{,}899.660, p < 0.05$) include a pattern of trajectories that have a significantly longer fixation time compared to cluster A.

	Dependent variable: Fixation Time		
	(1) Policy Model	**(2) Uniform Viewport Model**	**(3) Viewport Cluster Model**
Policy	8,895.227		
	(6,319.955)		
Viewport Time		0.294*	
		(0.139)	
Cluster B			3,175.735
			(3,933.241)
Cluster C			22,248.140***
			(5,532.456)
Cluster D			11,899.660*
			(4,742.844)
Cluster E			-11,378.720
			(24,849.240)
Constant	5,938.824	10,414.740***	11,378.720***
	(6,156.522)	(2,331.528)	(1,631.432)
R^2	0.006	0.013	0.060
Adjusted R^2 (imp. in %)	0.003	0.010 (+ 0.07)	0.049 (+ 4.87)
AIC	7,703.495	7,701.013	7,690.845
BIC	7,714.919	7,712.437	7,713.693
Note:			*p<0.05; **p<0.01; ***p<0.001

Table 3. Comparison of different approaches to identify fixation time

The usefulness of (uniform) viewport time to explain users' gaze has been documented in the literature (Lagun et al. 2014; Lagun et al. 2016). Our models confirm and extend this finding: Confirming RQ1, we show that clustered viewport trajectories explain users' total fixation duration, a measure of their visual attention. Finally, we note that the current ad viewability policy cannot sufficiently explain fixation time.

Explaining ad recall with viewport trajectories (RQ2): For advertisers, it is not necessarily relevant whether a consumer has paid attention to an ad, but also whether the ad has favorable downstream consequences, such as recall (RQ2). As a second comparison, we, thus, assess the models concerning their ability to model ad recall. Furthermore, our experimental setup enables us to compare the models to a benchmark model of fixation time as ground truth. We compute a logistic regression model for each of our metrics, to account for the binary nature of the dependent variable. Table 4 summarizes the coefficients as well as the indicators for goodness-of-fit (i.e., Nagelkerke R^2, Cox and Snell R^2, AIC, and BIC) for explaining aided recall (Models 1-4).

We find that the policy model (1) produces a null result, and does not help increase the likelihood of the model over the intercept-only baseline model. The reason for this is that through scrolling over the news articles, almost all ads were classified as viewable, as more than 50% of the ad's pixels were viewable for more than 1 second. This result has high face validity, as with normal reading behavior on websites, only ads at the very bottom of a page might not have been "viewable" at all (which was not the case in our experiment, where ads were embedded in the text). Therefore, a "viewability" model should be biased toward reporting a positive result (i.e. the majority of cases are classified as positive as the policy model would rarely qualify an ad as not seen).

	Dependent variable:							
	Aided Recall				**Unaided Recall**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	Policy Model	**Uniform Viewport Model**	**Viewport Cluster Model**	**Fixation Time Model**	**Policy Model**	**Uniform Viewport Model**	**Viewport Cluster Model**	**Fixation Time Model**
Policy	0.217				0.367			
	(0.506)				(0.768)			
Viewport Time		0.00003**				0.00002		
		(0.00001)				(0.00001)		
Cluster B			0.870**				0.567	
			(0.327)				(0.406)	
Cluster C			1.583**				1.534**	
			(0.526)				(0.476)	
Cluster D			-0.239				-0.007	
			(0.398)				(0.570)	
Cluster E			14.925				-12.664	
			(882.743)				(882.743)	
Fixation Time				0.00003***				0.00001*
				(0.00001)				(0.00000)
Constant	-0.357	-0.591**	-0.359**	-0.505***	-2.015**	-2.005***	-1.902***	-1.843***
	(0.493)	(0.190)	(0.134)	(0.134)	(0.753)	(0.266)	(0.196)	(0.177)
Nagelkerke R^2	0.001	0.033	0.076	0.099	0.001	0.014	0.054	0.022
Cox Snell R^2 (imp. In %)	0.001	0.025 (+ 2.4)	0.057 (+ 5.6)	0.074 (+ 7.3)	0.001	0.008 (+ 0.8)	0.032 (+ 3.2)	0.013 (+ 1.3)
AIC	463.571	455.319	450.335	437.986	295.641	293.242	291.132	291.522
BIC	471.187	462.935	469.375	445.602	303.258	300.858	310.173	299.139
Note:								*p<0.05; **p<0.01; ***p<0.001

Table 4. Comparison of different approaches to identify ad recall

The uniform viewport time model (2), instead, significantly increases the likelihood of the model ($Cox\ Snell\ R^2$ = 0.025; AIC = 455.319) and is associated with a higher probability of an ad to be recalled. Likewise, the proposed viewport trajectories model (3) is significantly different from the baseline model and additionally outperforms the policy and uniform viewport time model in terms of the likelihood of the model ($Cox\ Snell\ R^2$ = 0.057; AIC = 450.335) and increases the goodness-of-fit by 128% over the uniform viewport time model. Cluster B and, in contrast to the corresponding model on fixation time, C is significantly associated with a higher probability for an ad to be recalled. As expected, the model is outperformed in terms of Cox and Snell's R^2 value as the benchmark model which has been fitted on the fixation time (4, $Cox\ Snell\ R^2$ = 0.074; AIC = 437.986) with a gain in goodness-of-fit of 198% over the uniform viewport time model. The results for unaided ad recall (Models 5-8) are consistent with the results for aided recall. All effects reported above are robust to the estimation as a multi-level model with random effects for subject, ad as well as news article.

With this comparison, we extend and validate the usage of (uniform) viewport time to the domain of advertisement recall. Moreover, we can show that our proposed viewport trajectories model demonstrates a model fit that is on par with traditionally used metrics, such as eye-tracking. Finally, we can replicate the finding that the current ad viewability policy does not hold the formal test and does not inform the modeling of ad recall.

Conclusion and Implication, Limitations and Future Research

Conclusion and implications

Based on an eye-tracking study on mobile phones, our research highlights how a more granular utilization of the available viewport data might improve how ad attention can be measured. We offer three main findings relevant to publishers, advertisers, and ad researchers.

First, we find that ad viewing patterns differ by users and that these differences might be analytically utilized to explain ad attention. Based on extant literature, we empirically establish five different clusters, which differ in the way they engage with ads, of which only two deeply engage with the advertisement, showing a positive relationship between viewport time and fixation.

Figure 5 illustrates the receiver operating characteristic (ROC) curves for the predictions of our models (30% hold-out sample). In line with our models for explaining aided and unaided ad recall, the "viewability" policy model (50%) does not help to predict true recall, and shows a higher false-positive rate compared to the other models, as non-attentive segments would also be counted as ad exposure (AUC: 0.50). The eye-tracking-based "Fixation Time Model" performs best, identifying most recall correctly (AUC: 0.69)– but the data required for this model cannot be obtained in practice, as it would require all users to wear an eye-tracking device when exposed to ads. The viewport trajectories model (AUC: 0.58) outperforms the uniform viewport model (AUC: 0.55). Please note that the quasi-linear shape of the clustered viewport trajectories due to the categorical nature of the cluster membership (i.e., only five possible thresholds for plotting).

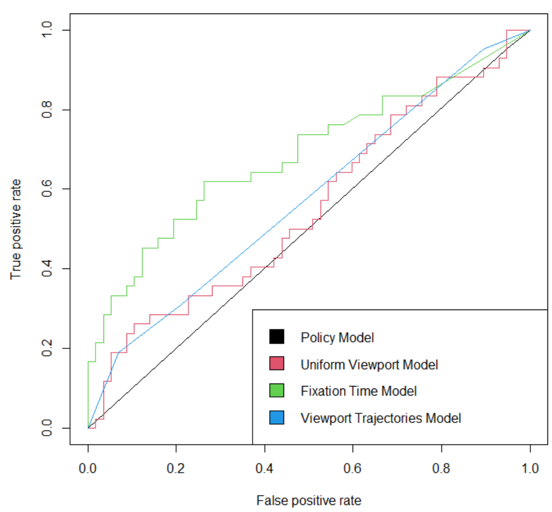

Figure 5. ROC curves for Policy, Uniform Viewport, Viewport Trajectories, and Eye Tracking models.

Besides highlighting the need for a clustered approach to measuring mobile ad attention, our findings also offer managerial opportunities. For instance, a user's ad viewing behavior might be used to recognize a specific cluster (e.g., active attention), which then can be used to adjust the ad content—for instance marking for the advertiser that this user is worth more (which would increase the cost per view for the publisher), or showing him/her different content (i.e., "morph" banners ads [Urban et al. 2014] to catch attention or present detailed information if attention is already there).

Second, methodologically, we show that a more granular reading of the viewport (+333%), especially if it also employs a clustering of users by their view patterns (+1633%), offers a better way to explain actual attention (here: actual fixations measured through eye-tracking) than established dichotomous policy models (i.e., the 50% rule). This offers multiple implications for researchers and practitioners alike: first, the present "viewability" model might be an insufficient measure of ad attention (i.e., the 50% policy). Further, a more granular reading of the viewport might also be a relevant input variable for the assessment of ad effectiveness, which currently still relies on data generated through the policy-model (Ghose and Todri-Adamopoulos 2016; Johnson et al. 2017). Further, our findings indicate that the viewport offers relevant data to analyze advertising effects, besides clickstreams (Bucklin and Sismeiro 2009) and, thus, constitute another promising source of "big data" for studying mobile advertising (Grewal et al. 2016).

Third, substantively, we are—to the best of our knowledge—the first study to show that for mobile phones as well as for ad attention, the process of visual attention iterates between exploration and focused attention (Otero-Millan et al. 2013). Specifically, we show that exploration predominantly happens on the lower part of the screen (where ads usually emerge into view), while focused attention (i.e., fixations) concentrates on the upper half of the screen. We replicate extant research showing that more fixations lead to more ad recall, but can also show that recall can be explained from viewport data alone. Managerially, this implies that placing ads on the top of a (mobile) webpage might not be ideal, as viewers cannot explore the latter and are, thus, also less likely to focus on them. As this finding might also be due to the setup (e.g., that ads had to be scrolled in first from the bottom), we would be cautious with this implication.

Limitations and future research and points for discussion

Our research is also limited in three dimensions, which future research should address. First, we are currently aggregating fixations and saccades on the advertisement level. Instead, both could be analyzed concerning their vertical position along the mobile phone screen. This would enable us to put the visual evidence from heatmap and gaze trail to a formal test and confirm the prevalence of areas of interest, where ads are explored versus fixated by users. Furthermore, fixations and saccades that are coded along the same coordinate system as viewport time observations, would allow for a more differentiated comparison of the two measures and possibly, the direct validation of our trajectories model.

Second, while time-series clustering in general and dynamic time warping in particular, is a useful framework for exploring underlying structures in sequential data, Hidden Markov Models have been found to produce better accuracy of sequence classification (Sajjan and Vijaya 2012) and would, thus, be an alternative method worth applying to the data at hand. Looking at the single trajectories (not included in the manuscript) we can further rule out the need for non-linear sequence alignment in our case. State of the art approaches to cluster sequential data rely on interweaving both methods and computing Hidden Markov Models based on the solutions from an initial dynamic time warping iteration (Yao et al. 2019), which would potentially increase the quality of the resulting cluster solution. Finally, gaze time and likely also viewport time is strongly related to the scrolling behavior of the user and the content structure of the website (Turner et al. 2015). Consequently, for a full evaluation of viewport time with the ultimate goal of predicting ad attention, both variables should be taken into account.

A managerially interesting extension of our research would be to compute the monetary effects of the three approaches. We currently use eye-tracking fixation time as the metric dependent variable, showing that clustered viewport data can better explain fixation time than other models do, but we cannot quantify a potential financial loss of a use of the "viewability" model from an advertiser's view (Hobbs 2016). To show the consequences of different payment mechanisms, one would have to reduce the granularity of the eye-tracking data based on a consensus of what minimum fixation time is required to count as valid attention, then fitting the different models on this dependent variable, using the latter to decide if a consumer paid attention or not and to calculate ad costs.

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