A Neural Perspective on the Determinants of Effective Video Advertisements

Pantelis Karavassilis
Rotterdam School of Management
Konstantinos Rigopoulos
Democritus University of Thrace, Department of Economic Sciences

Cite as:
Karavassilis Pantelis, Rigopoulos Konstantinos (2023), A Neural Perspective on the Determinants of Effective Video Advertisements. *Proceedings of the European Marketing Academy*, (117228)

Paper from the EMAC Regional Conference, Athens, Greece, September 27-29, 2023

EMAC
EUROPEAN MARKETING ACADEMY

A Neural Perspective on the Determinants of Effective Video Advertisements

Abstract

This study explores the interplay between the characteristics of video marketing content and consumers' attention. Consequently, it creates insights of the ideal set of characteristics that optimise attention and contribute to the success of video advertisements. By means of machine learning and computer vision techniques, computerised metrics for the independent variables (visual complexity, salience, brand prominence, duration) were generated. The novelty of this approach combined with the use of dynamic video stimuli and the focus on specific video advertisement characteristics could act as the foundation for research with far-reaching and long-lasting implications on how effectiveness of marketing stimuli is measured.

Keywords: Neuromarketing, Attention Based Marketing, Video Advertisements

1. Introduction

Nowadays information (i.e., video content) is being produced and consumed at an increasingly fast pace which results in a more rapid depletion of peoples' limited attention resources. Simultaneously, peoples' attention time span seems to diminish as a result of the increase in the rates of production and consumption of information/content (Lorenz-Spreen et al., 2019). As it was aptly put by Greenberger and Simon (1971): "a wealth of information creates a poverty of attention and a need to allocate that attention efficiently". These two effects work synergistically and have significant impact on marketing efforts; as Orquin & Wedel (2020) posit "understanding how to attract, retain, and guide consumers attention is paramount for the success of many businesses".

As a result, a new field called Attention Based Marketing (ABM) is beginning to gain traction as more research is being done and its research methodologies and measurement instruments become more accessible and refined. Orquin & Wedel (2020) defined ABM as a sub-discipline of marketing that investigates the impact of attention in optimizing marketing activities and consumer prosperity. To do so, it primarily relies on eye-tracking metrics such as fixations, saccades, gaze paths etc. As defined, ABM does not explicitly lie in the realm of what has been called Neuromarketing or Consumer Neuroscience. However, the main driver of research in this field, as the name suggests, is attention and specifically visual attention. In the case of video advertisements, the need for understanding the success drivers of online advertisements has been amplified by the parallel increase of the number of online video viewers (Statista, 2022). Therefore, it is perhaps now more important than ever to explore the interplay of video ad elements and how they contribute to attention and, by extension, the overall effectiveness of an ad in terms of sales and brand loyalty.

The objectives of analysing quantitative data from participants' who were exposed to video ad stimuli, were the following: (i) to measure the effects of brand salience to inter-subject correlation (ISC) i.e., attention; (ii) to identify the relationship between branding occurrence and branding attention; (iii) to examine the value of total brand salience in a video ad; and finally, (iv) to provide insights for reduce the risk and save time and money when creating a video ad.

2. Literature Review

Research in the field of ABM can be broadly defined as being either Descriptive or Prescriptive. The former aims to uncover how marketing practices affect attention while the latter is geared towards generating a set of best practices that can help marketers improve marketing efforts to optimally capture attention. In the domain of advertising, most current literature is generally of exploratory nature in the sense that it investigates how various aspects of advertisements affect attention, customer buying intention or advertisement liking. For example, Wang et. al., (2020) explored consumer attention, information processing, and purchase intention using eye-tracking and questionnaire methods. In another study, Simola et al., (2020) assessed the effectiveness of direct versus indirect messages. That is whether ads that explicitly portray the brand or product are more successful than ads that require customers to decode the message (Simola et al., 2020).

Another approach to ABM is research of prescriptive nature. Such research aims to provide a set of guidelines which can be used to optimise the applied business and therefore have greater impact on the applied business domain. For example, Pieters et al., (2007) examined how the surface size of design elements (text, price, brand etc.) affected eye fixations in printed retail promotion materials. However, Wedel & Pieters, (2008), indicate that further research is needed to explore additional types of non-moving visual stimuli apart from printed advertisements. Additionally, it is important to investigate dynamic forms of stimuli such as television commercials and advertisements on websites. The present study aims to build on this body of research by investigating how characteristics of dynamic stimuli affect consumers' attention and consequently the effectiveness of these stimuli. For Wedel & Pieters (2008) this type of research will be highly valuable considering the pervasiveness of dynamic stimuli in marketing practice. Moreover, tv advertisement characteristics like pacing or branding in them, are ready for study (Wedel & Pieters, 2008). In addition, in their recent study on ABM, Orquin & Wedel, (2020) mention that more work needs to be done in emerging areas of marketing which included video advertisements. Understanding the components of advertisements that contribute to increased attention could subsequently be translated into increased sales as demonstrated by Zhang et al. (2009) who studied feature ads and found a positive effect of gaze length on sales of the product in question.

Much of the research relating dynamic video stimuli, and the elements that comprise them, has used eye-tracking as a tool for measuring attention. However, attention can also be viewed in terms of its neural correlates. Furthermore, studying dynamic video stimuli with the help of neural measures has been extensively studied with promising results about the predictive power of these measures for population level outcomes (Barnett & Cerf, 2017; Chan et al., 2019; Christoforou, 2017).

3. Research Question and Hypotheses

As previously mentioned, the study at hand, develops a model that takes into consideration a set of online advertisement elements and explores how they contribute to overall ad effectiveness. Moreover, the model allows for prescribing best practices for marketing practitioners. To this end the main research question to be answered can be stated as follows: How do the various elements of online video advertisements contribute to overall advertising effectiveness?

The research question can be further broken into sub-questions addressing a particular characteristic of an online ad. Based on the research perused some of the most important characteristics of dynamic video stimuli are as follows: Visual Complexity, Salience, Brand Prominence, Salience and Time/Duration. Visual complexity in and of itself is a complicated concept that has been studied as early as the Gestalt Psychology Paradigm at the beginning of the 20th century and has now also been studied from a neural perspective (Donderi, 2006). Although visual complexity seems like an intuitive concept, one could easily gauge relying on their own perception, pinpointing an exact definition has proven difficult; perhaps precisely because it is an intuitive concept. Nonetheless, Snodgrass and Vanderwart (1980) tried by defining visual complexity as "the level of detail or intricacy of an image". Other approaches went on to define visual complexity as a set of dimensions or levels that taken together help determine the degree of visual complexity (Christoforou et al., 2017; Pieters et al., 2010). This report will take a similar aggregation approach to determine a measure for visual complexity.

Brand prominence is a measure that can, in broad terms, be defined as the extent to which a brand stands out while watching the video stimulus. It is a composite measure because it depends on elements such the size and location of the logo, as well as the duration of exposure and the timestamps of when the branding appear.

Salience essentially refers to the extent that a certain element, location, or pixel of a visual stimulus stand out from its surroundings. Salience is determined by attributes such as colour, orientation, movement, depth, brightness etc. (Koch & Ullman, 1985). It has been shown that salience is a good indicator of whether the element, location, pixel etc. is likely to grab attention. Time / duration is relatively more intuitive and easier to understand. It simply refers to the length of the video ad measured in seconds.

Hypotheses:

H1a: Intermediate levels of visual complexity in video advertisements leads to higher levels of inter-subject correlation compared to low levels of visual complexity.

H1b: Intermediate levels of visual complexity in video advertisements leads to higher levels of inter-subject correlation compared to high levels of visual complexity.

H2a: Intermediate levels of visual salience are associated with higher levels of inter-subject correlation compared to low levels of visual salience**.**

H2b: Intermediate levels of visual salience are associated with higher levels of inter-subject correlation compared to high levels of visual salience.

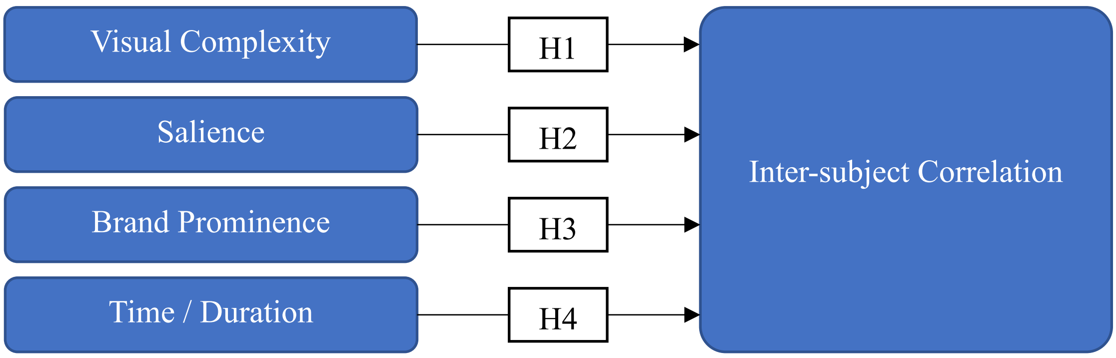
H3: A higher level of brand prominence leads to a higher degree of inter-subject correlation among participants compared to low levels of brand prominence.

H4: Inter-subject correlation is higher during the first few seconds of ad exposure compared to later points in time.

4. Materials & Methods

As discussed in the previous section, the aim of this study is to develop and test the quality of a model able to predict online ad effectiveness based on the predicted value of Brain Synchronicity. To do so, this chapter defines and operationalises a set of measures for the variables described in the "Research Question and Hypotheses" section and presented in the conceptual model below.

Exhibit 1: Conceptual Model



The data used for the present study was collected over the period 2019-2020. Specifically, participants were contacted through a database of contacts of a Neuromarketing vendor. All participants within the database have granted consent for storing their personal contact details and have agreed to being contacted for the purpose of participating in experiments. Participants are given the option of pre-arranged timeslots, which allowed enough time for researchers to set-up.
In preparation for the analysis the data was manipulated as follows:

- Firstly, a descriptive statistical and size frequency distribution analysis for each variable was performed. Doing so is informative of any additional steps that may be needed before additional processing.
- Change in mean ISC values and the independent variables along the video process time.
- Subsequently multiple correlation analysis among the variables was performed. Additionally, using multiple regression, the ISC value was regressed against the independent variables, to establish a predictive equation.

4.1. Dependent Measures – Neural Synchronicity

Literature refers to neural synchronicity in many different ways, however the basis of the measure is similar across all studies. For example, it has been called “Similarity” (Wyerjr et al., 2008), “Synchronisation” (Hasson et al., 2004) or Inter-subject Correlation - ISC (Cohen et al., 2017; Madsen et al., 2019).

4.2. Independent Measures - Visual Complexity, Salience, Brand Prominence, Salience and Time/Duration

The independent measures relevant to this report were generated by means of Machine Learning and Computer Vision techniques using a platform that analyses and quantifies visual stimuli.

4.3. Visual Complexity

As documented in the literature review, there is evidence for using the file size of images in JPEG/JPG formats as a proxy for visual complexity. This size was used as a proxy for visual complexity.

4.4. Salience

The salience metrics used in this report were calculated with the help of a platform that employees computer vision and machine learning to quantify visual. The model is used to generate heatmaps for any type of images (i.e., not necessarily included in the training dataset). For each input (a set of screenshots taken at 1 second intervals) two metrics relating to salience were calculated. Total salience refers to the sum of all salience-map pixel values assigned. In order to generate the total salience value, pixel values are first normalised. The value for mean salience is essentially an average score of salience. The formulas used to compute these metrics are presented below:

$$\begin{matrix} Total \\ Salience \end{matrix} = \sum Normalised\ \ spyne\ saliency\ map\ scores\ for\ all\ pixels\ in\ the\ frame$$

$$\begin{matrix} Mean \\ Salience \end{matrix} = \frac{\sum Normalised\ spyne\ saliency\ map\ scores\ for\ all\ pixels\ in\ the\ frame}{\sum\ Pixels\ in\ the\ whole\ frame}$$

4.5. Brand Prominence

In terms of brand prominence, there are two metrics used in the present report. The first one is branding attention and it is calculated by calculating numerical values for the pixels within the bounding box that encloses the corresponding brand logo or text for each commercial. Doing so allows for generating a metric that essentially calculates the degree to which that certain brand logo or text is likely to grab attention. This procedure follows the logic of (Huber et al., 2015).. The second metric, branding occurrence, is somewhat similar but differs in that instead of calculating the numerical values corresponding to each pixel, it simply uses the surface area of the bounding box around the brand logo/text which is then divided by the surface area of the whole frame/screenshot. It need be noted that for the instances where there are more than 1 logos/brand texts in the frame, the algorithm aggregates these logos/brand texts scores.

$$Branding\ Attention = \frac{\sum Normalised\ spyne\ saliency\ map\ scores\ for\ pixels\ within\ the\ bounding\ box}{\sum Normalised\ spyne\ saliency\ map\ scores\ for\ all\ pixels\ in\ the\ frame}$$

$$\begin{matrix} Branding \\ Occurence \end{matrix} = \frac{\sum Pixels\ in\ the\ bounding\ box}{\sum Pixels\ in\ the\ whole\ frame}$$

4.6. Time

Time is probably the most intuitive measure to understand since it simply refers to the duration of each video ad in seconds.

4.1 Results

The results of the analysis indicated that there is a negative relationship between the variable branding attention and ISC. This means that when the branding elements: logo and brand name saliency scores are high, the values of ISC tend to be lower.

It becomes apparent that, based on the coefficient signs, the ISC responded negatively with size increases in total salience and branding attention. Furthermore, ISC responded positively with jpg size. The important variable for the equation formation was the branding attention, followed by jpg size and total salience.

Additionally, a high correlation between branding occurrence and branding attention was observed. In the present study, branding occurrence was calculated by considering the surface area of a box drawn around the logo or text. The larger the box that encloses the logo or brand, the greater the branding occurrence value. On the other hand, branding attention is measured by summing the salience output scores within the bounding box.

Table 1: Detailed statistical output after the performance of multiple regression of ISC against the independent variables, all in logarithmic transformation.

Parameter Estimates				
Term	**Estimate**	**Std Error**	**t Ratio**	**Prob > |t|**
Intercept	-0,226578	0,037584	-6,03	<,0001*
Mean (Generalized Logarithm Transform total salience)	-0,290713	0,092409	-3,15	0,0021*
Mean (Generalized Logarithm Transform branding attention)	-0,457263	0,061333	-7,46	<,0001*
Mean (Generalized Logarithm Transform JPG KB Size)	0,4048511	0,089824	4,51	<,0001*

Table 2: Multivariate Pearson's correlation analysis:

	ISC	Salience	Attention	Occurrence
Salience	-0,1105			
Attention	-0,4826	0,0518		
Occurrence	-0,4708	0,0517	0,9994	
JPG Size	0,1390	0,4635	0,2123	0,2176

5. Discussion

The main purpose of the present study was to shed light on how certain features commercial video stimuli contribute to viewers' attention. The results of the analysis indicated that there is a negative relationship between the variable branding attention and inter-subject correlation (ISC). This means that when the branding elements: logo and brand name generate high saliency scores, the values of ISC tend to be lower. This is somewhat counterintuitive when compared to the results of (Pieters et al., 2007) which indicated that in optimising ads branding features should be enlarged. However, it need be noted that the inputs for their analysis were static feature ads rather than dynamic stimuli. A possible explanation for this result could relate to the concept of branding avoidance. Specifically, Teixeira et al., (2010) researched the effects of branding on peoples' decision to stop/avoid watching a commercial. They found that large, persistent and centrally located ad logos and texts would "notably" increase the likelihood that viewers disengage and stop watching the commercial. The size and duration of appearance of the logos and texts is closely related to the metric of branding occurrence as calculated in this report. This metric was found to be highly correlated with branding attention. Therefore, when considering these findings, the negative relationship between branding attention and ISC becomes more reasonable. For practitioners, this means that any branding present within the advertisement would need to be relatively subtle in order for viewers to not be deterred that the message presented is coming from an advertisement.

The high correlation between branding occurrence and branding attention poses and interesting finding with potential implications for practitioners working towards developing models for quantifying branding metrics in commercials. In the study at hand, branding occurrence was calculated by considering the surface area of a box drawn around the logo or text. The larger the box that encloses the logo or brand, the greater the branding occurrence value. On the other hand, branding attention is measured by summing the salience output scores within the bounding box. The high correlation between the two variables could allow practitioners to opt for the more intuitive surface-based metric rather than having to explain salience and how it is calculated.

The negative value of total salience is a surprising finding. For example, Huber et al., (2015) found that salience metrics for short videos play a significant role in determining whether attention will be sustained while watching. However, there are instances where high values of ISC and total salience occur simultaneously. These timestamps seem to overlap with the ending times of the videos. Unfortunately, this does not suffice to reject the stated hypothesis and generalize the effect. Huber et al., (2015) supported that it likely that an optimal level of salience is likely to exist and that striving to increase salience will likely render the stimuli “unwatchable”.

Based on the results presented in the previous section it is evident that visual complexity has a positive effect on ISC. In agreement with the study at hand, for design complexity, Pieters et.al (2010) found that it had a positive effect on ad performance since it increases attention and liking. However, it remains unclear to what extent the variable visual complexity of this analysis capture what Pieters et al., (2010) defined as feature complexity.

Exhibit 2: Summary of implications

Finding	Implication	For whom?
Negative effect between branding attention and ISC	Excessive branding by using big brand logos and placing them in a very prominent position might have negative effects on viewers’ attention and processing of the ad. Rather, subtle branding and more focus on the message will help with communicating the message.	Advertisers, Creative agencies.
A very high correlation between these two variables was observed.	For the purpose of quantitative modelling of ad performance opting for the simpler variable branding occurrence will allow researchers to avoid unnecessary complexity and lengthy descriptions of the model.	Researchers, Neuromarketing Vendors.
Negative effect between total salience and ISC	“Forcefully” increasing salience towards specific messages, logos and other elements in the ads will likely backfire because the advertisement will stop resembling a storyline and will lose viewers’ attention.	Advertisers, Creative agencies.
Positive effect between visual complexity and ISC	Every advertisement needs to be “visually complex” enough to arouse viewer and draw them to view the advertisement. Over simplified advertisements will likely not peak viewers interests while overcomplicated advertisements will make it hard for viewers to follow and pay attention	Advertisers, Creative agencies.
Overall research approach	Through this study, it was shown that insights can be drawn using an algorithmic approach by employing techniques such as machine learning and computer vision. This means that for research purposes, employing participants for testing advertisements is not strictly necessary so long as a robust model exists that can predict outcomes.	Researchers, Neuromarketing Vendors, advertisers, Creative agencies
Overall research approach	The present study introduces novelties to the body ABM body of research in that it studies specific advertisement characteristics of dynamic video stimuli and attempts to prescribe rather than describe the outcomes	Researchers, Neuromarketing Vendors, advertisers, Creative agencies

6. Limitations & Future Research

Despite its implications, this research is subject to limitations. In terms of the video inputs used, the advertisements were based on the available data available to the Consumer Neuroscience vendor from which it was obtained. Ideally, a set of both "successful" and "unsuccessful" advertisements from various sources would have been used.

Even though this study's approach does incorporate the time dimension, it only does so on an aggregate level. That is, both the dependent and independent variables are mean values of the video advertisements' metrics, on a second-to-second basis. This leads to a certain degree of information loss which may hinder more granular comparisons between the different advertisements.

In future research, the present experimental approach can be expanded by incorporating additional video advertisement characteristics such as: Pacing or soft/hard sell advertisements. Pacing refers to speed with which scenes are presented in the dynamic video stimulus i.e., online video advertisements (Lang et al., 1999). With regards to "soft-sell" or "hard-sell" tactics (Teixeira et al., 2010), intense branding, suggestive language and call to actions defines a hard-sell tactic while soft-sell tactics are more subtle. Therefore, it would be interesting to investigate whether this has implication on attention i.e., ISC.

As this report demonstrates, the groundwork for the effect of video advertisement characteristics has been set. Breakthroughs in this direction could set the stage for a paradigm shift in marketing wherein success of marketing activities could be predicted prior to launching campaigns.

7. References

Barnett, S. B., & Cerf, M. (2017). A Ticket for Your Thoughts: Method for Predicting Movie Trailer Recall and Future Ticket Sales Using Neural Similarity among Moviegoers. *Journal of Consumer Research*, ucw083. https://doi.org/10.1093/jcr/ucw083

Chan, H.-Y., Smidts, A., Schoots, V. C., Dietvorst, R. C., & Boksem, M. A. S. (2019). Neural similarity at temporal lobe and cerebellum predicts out-of-sample preference and recall for video stimuli. *NeuroImage*, *197*, 391–401. https://doi.org/10.1016/j.neuroimage.2019.04.076

Christoforou, C. (2017). Your Brain on the Movies: A Computational Approach for Predicting Box-office Performance from Viewer's Brain Responses to Movie Trailers. *Frontiers in Neuroinformatics*, *11*, 13.

Christoforou, C., Papadopoulos, T. C., Constantinidou, F., & Theodorou, M. (2017). Your Brain on the Movies: A Computational Approach for Predicting Box-office Performance from Viewer's Brain Responses to Movie Trailers. *Frontiers in Neuroinformatics*, *11*, 72. https://doi.org/10.3389/fninf.2017.00072

Donderi, D. C. (2006). Visual complexity: A review. *Psychological Bulletin*, *132*(1), 73–97. https://doi.org/10.1037/0033-2909.132.1.73

Greenberger, M., Johns Hopkins University, & Brookings Institution (Eds.). (1971). *Computers, communications, and the public interest*. Johns Hopkins Press.

Hasson, U., Nir, Y., Levy, I., Fuhrmann, G., & Malach, R. (2004). Intersubject Synchronization of Cortical Activity During Natural Vision. *Science*, *303*(5664), 1634–1640. https://doi.org/10.1126/science.1089506

Huber, R., Scheibehenne, B., Chapiro, A., Frey, S., & Sumner, R. W. (2015). The influence of visual salience on video consumption behavior: A survival analysis approach. *Proceedings of the ACM Web Science Conference*, 1–2. https://doi.org/10.1145/2786451.2786507

Koch, C., & Ullman, S. (1985). Shifts in selective visual attention: Towards the underlying neural circuitry. *Human Neurobiology*, *4*(4), 219–227.

Lorenz-Spreen, P., Mønsted, B. M., Hövel, P., & Lehmann, S. (2019). Accelerating dynamics of collective attention. *Nature Communications*, *10*(1), 1759. https://doi.org/10.1038/s41467-019-09311-w

Madsen, J., Margulis, E. H., Simchy-Gross, R., & Parra, L. C. (2019). Music synchronizes brainwaves across listeners with strong effects of repetition, familiarity and training. *Scientific Reports*, *9*(1), 3576. https://doi.org/10.1038/s41598-019-40254-w

Orquin, J. L., & Wedel, M. (2020). Contributions to attention based marketing: Foundations, insights, and challenges. *Journal of Business Research*, *111*, 85–90. https://doi.org/10.1016/j.jbusres.2020.02.012

Pieters, R., Wedel, M., & Batra, R. (2010). The Stopping Power of Advertising: Measures and Effects of Visual Complexity. *Journal of Marketing*, *74*(5), 48–60. https://doi.org/10.1509/jmkg.74.5.48

Pieters, R., Wedel, M., & Zhang, J. (2007). Optimal Feature Advertising Design Under Competitive Clutter. *Management Science*, *53*(11), 1815–1828. https://doi.org/10.1287/mnsc.1070.0732

Simola, J., Kuisma, J., & Kaakinen, J. K. (2020). Attention, memory and preference for direct and indirect print advertisements. *Journal of Business Research*, *111*, 249–261. https://doi.org/10.1016/j.jbusres.2019.06.028

Statista (2022). Digital ad spend worldwide 2026, (n.d.). Retrieved from https://www.statista.com/statistics/237974/online-advertising-spending-worldwide/#:~:text=As%20of%202022%2C%20the%20internet,accounting%20for%2062%20percent%20of (last accessed April 22, 2023)

Snodgrass, J. G., & Vanderwart, M. (1980). A standardized set of 260 pictures: Norms for name agreement, image agreement, familiarity, and visual complexity. *Journal of Experimental Psychology: Human Learning and Memory*, *6*(2), 174–215. https://doi.org/10.1037/0278-7393.6.2.174

Teixeira, T. S., Wedel, M., & Pieters, R. (2010). Moment-to-Moment Optimal Branding in TV Commercials: Preventing Avoidance by Pulsing. *Marketing Science*, *29*(5), 783–804. https://doi.org/10.1287/mksc.1100.0567

Wang, Q., Ma, D., Chen, H., Ye, X., & Xu, Q. (2020). Effects of background complexity on consumer visual processing: An eye-tracking study. *Journal of Business Research*, *111*, 270–280. https://doi.org/10.1016/j.jbusres.2019.07.018

Wedel, M., & Pieters, R. (2008). A Review of Eye-Tracking Research in Marketing. In N. K. Malhotra (Ed.), *Review of Marketing Research* (Vol. 4, pp. 123–147). Emerald Group Publishing Limited. https://doi.org/10.1108/S1548-6435(2008)0000004009

Wyerjr, R., Hung, I., & Jiang, Y. (2008). Visual and verbal processing strategies in comprehension and judgment. *Journal of Consumer Psychology*, *18*(4), 244–257. https://doi.org/10.1016/j.jcps.2008.09.002

Zhang, J., Wedel, M., & Pieters, R. (2009). Sales Effects of Attention to Feature Advertisements: A Bayesian Mediation Analysis. *Journal of Marketing Research*, *46*(5), 669–681. https://doi.org/10.1509/jmkr.46.5.669