Online Advertising Suppresses Visual Competition during Planned Purchases

RALF VAN DER LANS
RIK PIETERS
MICHEL WEDEL

Online advertising can help consumers to implement their purchase intentions on shopping websites. This research tests the hypothesis that online advertising can speed-up product search by visually suppressing competing products rather than by enhancing the target product on websites that lack a systematic visual organization. First, a survey shows that searching for products on a shopping website after having clicked on an online ad is a common experience. Second, a lay-theory experiment shows that the majority of participants incorrectly predict that online ads do not affect product search, but if these ads do, product search would be independent of shopping website design. Third, three eye-tracking and two search-time experiments reveal that online ads with an image of the target product improved search speed by about 25%, for websites without a systematic visual organization of products. Improved search speed was primarily due to faster rejection of competing products because the ads helped to perceptually suppress their color features. These results provide new insights into online advertising effects, the fundamental search processes through which these accrue, and how ads can support consumers in making their planned purchases.

Keywords: product search, intention implementation, online advertising effects, eye tracking, attention

The use of online ads continues to grow rapidly, as does the need to understand how these ads influence consumers' behavior. Online advertising generated $124.6 billion in revenues in 2019 in the United States, a 15.9% increase from the year before (IAB 2020, 4). Compared to offline advertising, the effects of online ads can be measured more accurately using clickstream data. This has resulted in a better understanding of the positive and negative effects of online ads on consumers' browsing behavior. For instance, online ads were shown to impact web page visits (Hoban and Bucklin 2015; Rutz and Bucklin 2012; Sahni, Narayanan, and Kalyanam 2019), click-through rates (Chatterjee, Hoffman, and Novak 2003; Kireyev, Pauwels, and Gupta 2016), and purchase behaviors (Breuer and Brettel 2012; Lewis and Reiley 2014; Li and Kannan 2014; Manchanda et al. 2006; Xu, Duan, and Whinston 2014). Some research has cast serious doubts on the effectiveness of online advertising because such ads can be annoying and distracting (Cho and Cheon 2004; Goldstein et al. 2014; Thota, Song, and Biswas 2012), so that frequent exposure may lead to fewer website visits (Chae, Bruno, and Feinberg 2019) and lower click-through rates (Försch and de Haan 2018).

Yet, despite their importance, clickstream data record the decisions that consumers make on websites rather than the processes that give rise to these decisions, and such

Ralf van der Lans (rlans@ust.hk) is a professor of marketing at the Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong. Rik Pieters (pieters@uvt.nl) is a professor of marketing at the Tilburg University, P.O. Box 90153, The Netherlands. Michel Wedel (mwedel@umd.edu) is a Distinguished University Professor and PepsiCo Chair in Consumer Science, Smith School of Business, University of Maryland, College Park, MD 20742-1815, USA. Please address correspondence to Ralf van der Lans. A grant from the Hong Kong Research Grant Council (GRF645511) supported this research. Supplementary materials are included in the web appendix accompanying the online version of this article.

Editors: Vicki G. Morwitz and J. Jeffrey Inman

Associate editor: Olivier Toubia

Advance Access publication March 26, 2021

 • Vol. 48 • 2021
DOI: 10.1093/jcr/ucab017

process insight is crucial in understanding, predicting, and potentially shaping consumers' decisions to click. Eye-tracking research holds promise of providing such process insights. As a case in point, eye-tracking experiments found that people who were shopping online actively avoided looking at distracting ads on the same page (Drèze and Hussherr 2003) and that the row-column orientation of shopping sites impacted eye movements during information search (Shi, Wedel, and Pieters 2013). Almost all online purchase decisions involve some amount of visual product search, especially in the final stages just prior to implementing one's decision to purchase. Van der Lans, Pieters and Wedel (2008a, 2008b) used eye-tracking experiments to investigate such visual product search, but they did not study if and how advertising affects it.

Often, consumers search and inspect candidate products on a website, with the purpose of finding the product that they have already decided to buy among the available set (Park and Sela 2020). This occurs, for example, when going online to buy a fragrance as a present for a friend, knowing that the recipient likes Estée Lauder products, or when visiting an online retailer's website to buy the pair of Ray-Ban sunglasses seen earlier in an online display ad. One of Rossiter and Percy's (1997) five advertising communication goals, "brand purchase facilitation," is particularly relevant in this context. It focuses on how advertising can help the implementation of an already formed purchase intention while searching for the chosen product among a set of competitors. This communication goal is crucial in online advertising contexts where consumers commonly click on an online ad that brings them to a shopping website. Following the setup of Park and Sela (2020), in a survey ($n = 306$) that we conducted 89% of consumers reported having had the experience of searching for a product on a shopping site after clicking an online ad, and 34% of consumers reported that this happens frequently to them (details in web appendix A). Eye-tracking research has not yet been applied to investigate if and how online ads can affect subsequent product search for a chosen product on shopping websites, yet it offers the potential to provide novel insights.

Because the time interval between exposure to an online ad and subsequent online shopping is usually brief, we expect that well-designed ads can facilitate product purchase, namely, by improving the speed with which consumers can find the target product among the competition (see web appendix B for examples of online ads with links to shopping websites). Such short-term effects of advertising have not been previously studied. Key unanswered questions are if and when online advertising can help consumers to implement their intentions and through which processes this takes place. We propose that online ads can facilitate product search by helping consumers to more rapidly identify the product that they intend to buy ("target identification") or reject competing products that they do not intend to buy ("competitor rejection"). This distinction between target identification and competitor rejection during target search is critical. Clearly, rapid identification of the target product during search is important because it facilitates the implementation of intentions. But online ads that facilitate the efficient rejection of competing products will limit the ability of these products to intrude, slow down the search process, cause irritation, and may even obstruct consumers from making a purchase altogether. For retailers, the effect of online advertising on the ease with which consumers can find products on their shopping websites is an important reason to invest in the design and layout of these shopping sites, but no research has yet addressed these issues.

Our research does not examine the influence of ads on the likelihood or incidence of making unplanned purchases (Inman, Winer, and Ferraro 2009; Stilley, Inman, and Wakefield 2010). Instead, it examines if and how ads can support planned purchases when consumers try to find the product they intend to buy among the competition on a shopping website. This is new. Prior research has emphasized goal setting, intention formation and planning of purchases, but less so intention implementation and plan execution (Baumgartner and Pieters 2008; Gollwitzer and Sheeran 2006; Huang and Hutchinson 2013 for reviews). No research to date has studied how advertising can support consumers in making planned purchases.

We hypothesize, motivated in detail later, that online ads that contain an image of the target branded product (vs. ads with the brand name, logo and a general pictorial) speed-up product search by visually suppressing competing products rather than by enhancing the target product on websites that lack a systematic visual organization. In addition, we explore the persistence of these effects of online ads on search. We develop a new eye-tracking based measure of color congruent attention (CCA) that captures top-down visual enhancement and suppression of visual features and that can be readily used for further theory testing and advertising management.

Three controlled eye-tracking experiments and two large scale search-time experiments test the hypothesis. The experiments examine the effects that online ads have on the time to find the target product among its competitors, and the attentional processes that contribute to search efficiency. Eye-tracking experiment 1 investigates the effects of the presence of a product image in the ad and its contrast with the ad background. Eye-tracking experiment 2 investigates the persistence of the effect of the ad on search speed across several intervening search tasks, and it examines the moderating effect of the organization of shopping websites (unorganized or visually organized). Eye-tracking experiment 3 examines in more detail the moderating effect of the organization of shopping websites (unorganized, visually, or semantically organized). All three eye-tracking experiments use Bayesian mediation analyses to investigate the role of (target-distractor) color congruency as the underlying mechanism. The two search-time experiments replicate the findings under less controlled conditions, using incentivized tasks in which participants are asked to implement intentions for a product of their own choice rather than a commissioned choice. No other studies than those reported here were conducted.

VISUAL SEARCH

Consumers frequently engage in visual product search, often multiple times a day (Milosavljevic et al. 2012; Park and Sela 2020; van der Lans et al. 2008a). Search for products on shopping websites of manufacturers and retailers, and on those that search engines compile, can be challenging due to the clutter of competing products or the organization of the website. The efficiency of search critically determines the likelihood that consumers successfully implement their plan to purchase the intended product. The time needed to find a target product, as a measure of search efficiency, has been used as the key outcome measure in psychological research on visual search (Pashler, Johnston, and Ruthruff 2001; Wolfe and Horowitz 2004). In addition to search-time measures, eye movements hold the promise of identifying the rapid, unobserved attentional mechanisms that account for differences in search efficiency (van der Lans and Wedel 2017). The present research uses three eye-tracking experiments to infer the attentional processes during search, and two search-time experiments to further test our hypothesis about how online ads for the target product visually suppress competing products.

Imagine a consumer visiting a shopping website, with the intention to buy a specific product. The shopping website contains a choice set that includes the target product and various competing products. The choice set may contain different brands and different versions or SKUs of the same brand, such as versions of a brand of shampoo (eye-tracking experiment 1), sunglasses, fragrances, or shoes (eye-tracking experiments 2 and 3, and the two search-time experiments), which makes search challenging. In the sequel, we refer to these brand/SKU combinations as "products." During visual search, consumers successively fixate on the various products on the shopping website with their eyes until they identify and choose the target product. During an eye fixation, the eye is fairly still and the brain extracts information from a small region (2° of visual angle) on the display. The duration of an eye fixation ranges from 100 to 500 ms and, although mostly beyond conscious control, varies with processing load, being shorter during easier search tasks (van der Lans, Wedel, and Pieters 2011). In-between fixations, the eyes make fast saccades (around 20–40 ms), during which vision is actively inhibited to prevent visual blurring.

Bottom-Up Salience and Top-Down Modulation

Locating candidates during product search is influenced by bottom-up (stimulus) factors, in particular basic perceptual features such as color and luminance (Wolfe and Horowitz 2004). The human brain represents these features in spatial maps (Itti and Koch 2001; Treisman and Gelade 1980; van der Lans et al. 2008b; Wolfe 1994; Wolfe and Horowitz 2004), which are integrated into an overall salience map, sometimes called an activation or priority map. Salience is a "bottom-up" or stimulus property (Itti and Koch 2001) that is spatially represented in several areas in the visual brain (Gottlieb, Kusunoki, and Goldberg 1998; McPeek and Keller 2002; Thompson and Bichot 2005). Some of these areas are involved in guiding eye movements, which explains why consumers tend to fixate and prefer salient products in brief, repeated choice tasks (Milosavljevic et al. 2012).

Salience of stimuli facilitates visual search especially if the target is the only salient item on the display. In other situations, it is important to focus the eyes on locations with features that are relevant to the current goal or task and to ignore those that are irrelevant, which occurs via top-down modulation (Duncan, Humphreys, and Ward 1997; Zanto and Rissman 2015; Zehetleitner et al. 2013). Such top-down modulation involves enhancement (or "activation") of relevant and suppression (or "inhibition") of irrelevant visual information (Sawaki and Luck 2010). Empirical support for top-down suppression of features comes from differences in response times in search tasks (Caputo and Guerra 1998), neural activity (Ipata et al. 2006), and eye-movement recording (Gaspelin and Luck 2018).

In the context of the present research, exposure to a product in an ad creates a memory trace for its basic features, which facilitates top-down modulation in subsequent product search. For instance, the blue color of a shampoo bottle may improve search speed if it is enhanced during search for the product, while other colors such as red are suppressed. Locations in the feature maps in the visual areas of the brain are thus enhanced or suppressed top-down based on their task relevance. Top-down modulation results in the guidance of eye movements toward objects that are visually similar to the target. This has been shown for objects that share edges or shapes with the target (Becker 2011), but search is faster especially when targets and distractors are distinguished by one (Luria and Strauss 1975) or more colors (Stroud et al. 2019). Complex distractors, that differ from a target on multiple features, can be rejected more rapidly than simple ones (Godwin et al. 2015). While semantic similarity of distractors to a target may also affect fixations on them (Schwarz and Eiselt 2012), the impact of visual similarity is much larger (Godwin, Hout, and Menneer 2014). Research has thus revealed the effect of distractor-target similarity on the speed with which distractors can be rejected during search. Yet, the extant literature has been based on comparatively simple stimuli in fast, repeated tasks and has not shown the impact of prior exposure to the target, such as via advertising.

Target Acceptance and Competitor Rejection

Search for a complex product among its competitors comprises a series of fast "micro-decisions" where consumers ask themselves "is this the product that I'm looking for?," with the correct answer being "no" if the attended product is a competitor, and "yes" if the attended product is the target. Prior exposure to an ad can speed-up search for a target product on a shopping website with competitors by speeding up the rejection of competing products when attending to them (i.e., competitor rejection) and speeding up the acceptance of the target product when attending to it (i.e., target acceptance). Advertising can influence both processes through top-down modulation of perceptual features.

Prior exposure to an online ad may render competitor rejection more efficient because competitors' features are suppressed top-down. This would result in a consumer making *fewer eye fixations on competitors* because fewer fixations would be needed to determine that these products are not what the person is looking for. At the same time, *eye fixations on competitors might be shorter* because less cognitive effort would be needed to reject a product as being a competitor rather than the target (Smith and Ratcliff 2004; Towal, Mormann, and Koch 2013).

Prior exposure to online ads can speed up identification of the target through top-down enhancement of its features. This would result in *fewer and shorter eye fixations on the target* product before the consumer confirms to have found it. This is more likely to occur when the ad shares perceptual features with the target product, rather than semantic features such as its name, in particular when the ad has a visual image of the target product. Pictorial cues are likely to result in stronger and more detailed neural activation as compared to semantic cues, which evidence accumulation models predict to facilitate target identification (Smith and Ratcliff 2004; Wedel and Pieters 2015).

The literature does not yet converge on whether target acceptance or competitor rejection prevails during product search. Measuring search times for simple multi-element displays, Maljkovic and Nakayama (1994) inferred that perceptual priming facilitated both of these attentional processes, but that the effects on target acceptance were stronger. In contrast, while Lamy et al. (2008) also found that both target enhancement and distractor suppression mediated search efficiency, they did not find substantial evidence that either one dominated. While targets and distractors in the research by Lamy et al. (2008) differed on a single feature, Geyer, Müller, and Krummenacher (2006) used targets and distractors comprising conjunctions of features. They did not find evidence for target enhancement but did find evidence for distractor suppression. Relatedly, Arita, Carlisle, and Woodman (2012) found stronger effects of target enhancement for simple displays with few distractors, but the effects of competitor suppression became stronger for complex search displays with more distractors. Eye-tracking experiments indicated that priming reduced the number of eye fixations on distractors (Becker and Horstmann 2009; McPeek, Maljkovic, and Nakayama 1999).

Because shopping websites are complex, with multiple competitors from which the target can usually only be distinguished based on a conjunction of features, we predict that the effect of online ads on competitor rejection dominates. Top-down suppression of competitors' features due to prior exposure to an ad that contains an image of the product would allow consumers to reject competing products more efficiently. An important question is whether the actual image of the product (perceptual priming), for example, of Nike shoes, or the brand logo (semantic priming), Nike's white swoosh, facilitates top-down suppression most. Semantic cues may also activate perceptual features via conceptual priming, for instance when Nike's brand name primes the white swoosh symbol. In view of the precedence of perceptual priming (Folk, Remington, and Johnston 1992; Wolfe 1994; Wolfe and Horowitz 2004), and in line with findings on the dominance of visual over semantic target-distractor similarity on search (Godwin et al. 2014), we expect that exposure to an ad with an image of the product itself most strongly enhances features of the target and suppresses those of competitor products.

The process of top-down enhancement of targets and suppression of competitors may be moderated by the structure of the assortment on which search takes places, that is, the similarity of the target with competitors and the organization of the shopping website. On average, visual search is likely to be faster on websites with stimuli organized according to similarity of perceptual features, in particular when distractors are similar among themselves but different from the target. Those effects of the grouping of displays comprised of simple stimuli were first shown by Duncan and Humphreys (1989). Geyer, Zehetleitner, and Müller (2010) showed that, in repeated search tasks, the display context can speed up the selection of targets by enhancing feature contrast. Organizing targets and competitors based on their perceptual features globally increases the conspicuousness of regions with products that are similar to the target. This makes a smaller subset of similar products salient, including the target. In such a grouped display; however, the conspicuousness of the target relative to the competitors is reduced locally among the subset of visually similar products, which would hinder search and attenuate the effect of the prior exposure to the ad. Therefore, a website organized in terms of perceptual features may attenuate the search efficiency gains caused by the online ad, compared to a display that is unorganized or based on semantic features (such as alphabetically).

In sum, we hypothesize that online ads that include a product image improve the speed of product search on shopping websites by enabling more efficient rejection of competitors, an effect that is attenuated if the target product appears among a subset of competitors that are visually similar, due to the organization of the shopping site. Eye-tracking analysis will enable us to reveal the process by which this occurs. We first describe two new sets of eye-tracking measures that we developed for that purpose.

EYE-TRACKING MEASURES

Eye-Tracking Decomposition of Search Time

In eye-tracking experiments of visual search, the total search time, Y, can decomposed into four components in the vector Y^{COMP}: (1) the number of fixations on the target product (Y_1^{COMP}); (2) the average fixation duration on the target product (Y_2^{COMP}); (3) the number of fixations on competitor products (Y_3^{COMP}); and (4) the average fixation duration on competitor products (Y_4^{COMP}). It holds approximately (barring eye blinks, saccades, minor eye movements) that $\mathrm{Y} \approx Y_1^{COMP} Y_2^{COMP} + Y_3^{COMP} Y_4^{COMP}$. This decomposition enables us to identify two aspects of the search process that account for differences in overall search time: (1) target acceptance (Y_1^{COMP} and Y_2^{COMP}) and (2) competitor rejection (Y_3^{COMP} and Y_4^{COMP}).

Eye-Tracking Measure of CCA

In addition, to investigate the extent to which the effects of the ads on these four eye-movement components are mediated by the top-down modulation of perceptual features, we propose a new measure of CCA. This measure captures the extent to which participants are inclined to fixate products that look like the target. We focus on color because target-distractor similarity in terms of color has been shown to have stronger effects on search than similarity in terms of other features (Becker 2011; Luria and Strauss 1975; Stroud et al. 2019). Specifically, using standard image processing software, pixel-level feature values are derived from the image of a shopping website using the CIELAB color space. Compared to RGB, the CIELAB measure is a closer representation of how humans perceive colors and luminance (Connolly and Fleiss 1997).[1] For each pixel in an image, it decomposes an infinite number of colors into three dimensions: (1) luminance L (black to white), (2) color channel a (green to red), and (3) color channel b (blue to yellow). The average value of the luminance and a- and b- color channels is calculated across all pixels of an AOI containing product p ($p = 1, \ldots, P$, with P the total number of products on the website), denoted by L_p, a_p, and b_p. This calculation is based, for each product p, on a ($R \times C$) matrix indicating the pixels on the image of the website with row size R and column size C. The elements of this matrix $\mathrm{AOI}_p(row, column)$ are equal to one if the pixel in the corresponding row and $column$ was part of the AOI of product p, and zero otherwise. Then, L_p, a_p, and b_p are computed as:

$$L_p = \frac{\sum_{row=1}^{R} \sum_{column=1}^{C} L(row,column) \cdot \mathrm{AOI}_p(row,column)}{\sum_{row=1}^{R} \sum_{column=1}^{C} \mathrm{AOI}_p(row,column)}, \quad \textbf{(1)}$$

$$a_p = \frac{\sum_{row=1}^{R} \sum_{column=1}^{C} a(row,column) \cdot \mathrm{AOI}_p(row,column)}{\sum_{row=1}^{R} \sum_{column=1}^{C} \mathrm{AOI}_p(row,column)}, \quad \textbf{(2)}$$

$$b_p = \frac{\sum_{row=1}^{R} \sum_{column=1}^{C} b(row,column) \cdot \mathrm{AOI}_p(row,column)}{\sum_{row=1}^{R} \sum_{column=1}^{C} \mathrm{AOI}_p(row,column)}, \quad \textbf{(3)}$$

where $L(row,column)$, $a(row,column)$, and $b(row,column)$ indicate the CIELAB L, a, and b values of the pixel in the corresponding row and column on the image of the website.

For participant c, due to ad exposure, the three luminance and color values may be enhanced for the target product and/or suppressed for competitors. In the latter case, consumers are less likely to fixate products that have features dissimilar from the target product. To operationalize this top-down modulation process for each participant c, the negative of the natural logarithm (ln) of the average Euclidean distance between the three CIELAB dimensions of a fixated product p and the target product $\tilde{p}_c$ is calculated. The natural logarithm reflects Weber's law of the perception of differences (Shen 2003), and the minus sign is added such that higher values correspond to stronger (more effective) enhancement of the target and suppression of competitors. This results in the following measure for CCA:

$$\mathrm{CCA}_c = -\ln \left(1 + \sum_{i \in \text{product } p} \sqrt{\left(L_{p_{ci}} - L_{\tilde{p}_c}\right)^2 + \left(a_{p_{ci}} - a_{\tilde{p}_c}\right)^2 + \left(b_{p_{ci}} - b_{\tilde{p}_c}\right)^2} / n_c \right). \quad \textbf{(4)}$$

1 Across all experiments, we obtain similar results if the color congruent attention measure is derived in RGB-color space (see web appendix C). As predicted, the measure constructed from bottom-up salience (Itti and Koch 2001), which differs between stimuli but is constant across participants, did *not* mediate our results (see web appendix D). This implies that top-down modulation operates on individual perceptual features rather than on the overall salience (Bacon and Egeth 1994; Folk et al. 1992; Lien et al. 2008).

In equation 4, the summation is over "$i \in$ product p," referring to all fixations i that landed on a pixel belonging to the AOI containing product p (i.e., $\text{AOI}_p(row_i, column_i) = 1$ for product $p \in \{1, \ldots, P\}$, with row_i and $column_i$ indicating the location of fixation i on the website). To compute the average, the sum of Euclidean distances is divided by n_c, which is to the total number of fixations of participant c that landed on the AOI of a product. Hence, higher values (close to zero) of CCA_c indicate strong top-down suppression, because participant c fixates on average only products that are similar in color to the target, while strongly negative values reflect weak top-down suppression.

EXPERIMENTS

We designed three eye-tracking experiments and two online search-time experiments to test our theory. Eye-tracking experiment 1 makes three contributions. First, it tests our hypothesis about target acceptance and competitor rejection mechanisms during product search, under strictly controlled conditions for a single ad and one product category. Second, it investigates two ad characteristics that might account for the potential search efficiency gains due to ad exposure: the presence of a product image (picture) in the ad and the product image's (color) contrast with the background. We expect online ads to produce efficiency gains when the ad contains a product image of the target product because the image enhances perceptual features present in the target, and that a (color) contrasting background may attract attention to the product image, thereby enhancing its features and improving search efficiency more. Third, the experiment investigates the mediating role of our new measure of top-down modulation: CCA.

Eye-tracking experiment 2 builds on this in three ways. First, for generalizability, it examines the effects of ads for each of five different product categories appearing in two different search engines. Second, it uses shopping websites that include both textual and visual product information. Third, it examines the moderating effects of the organization of the shopping website (unorganized or organized according to visual features) and the time lag between ad exposure and search task.

Eye-tracking experiment 3 further generalizes and extends the second experiment. First, it investigates search benefits in an incentivized search task across three product categories. Second, it delves deeper into the moderating role of the organization of the shopping website by comparing unorganized, perceptually (visual), and semantically (alphabetical) organized shopping websites.

The two search-time experiments are conducted using incentivized target search tasks and large participant samples. These build on the eye-tracking experiments by testing the hypothesis that online ads with an image of the target only reduce search time if competitors contain perceptual features that differ sufficiently from the target, by manipulating the color congruency of the shopping websites.

We report on eye-tracking experiments 1 and 2 and search-time experiment 1 in detail. We summarize the results of eye-tracking experiment 3, a lay-theory study, and search-time experiment 2 and refer to the web appendix for details on these studies.

EYE-TRACKING EXPERIMENT 1

Participants and Stimuli

A sample of 166 undergraduate students from a public university participated for course credit (M age = 22). The sample size for this and the following eye-tracking experiments was determined by the constraints of available participants and eye-tracking equipment. Participants were randomly assigned to one of the five conditions of a 2 (product image: yes–no) × 2 (color contrast: high–low) + 1 (control condition: no ad) between-participants design. Four different versions of an online ad (from now on called "ad") were designed by adapting an existing ad for Dove shower gel used in Dove's award winning "Real Beauty" campaign. The ad was adapted to test for the influence of (1) product image: either an image of the package and the brand logo or only the brand logo was present in the ad and (2) color: the background color in the ad was similar to the dominant color of the pack (blue) or not. Second, an image of a stylized shopping website (from now on called "search display") was produced on which forty different products were present (five brands, each with multiple versions or SKUs). Figure 1 shows one of the ads (all ads are in web appendix E) and the search display.

Tasks and Measures

Participants were individually seated in front of a 21-inch LCD computer screen (1024 × 1280 pixels) on which the stimuli were presented full-screen and in full-color. After a (9-point) eye-movement calibration and a warm-up task, participants saw a series of sixteen ads for various categories and products. Ads were in random order, except for the target Dove ad, which appeared toward the end of the sequence in position 14. Ad exposure duration was 10 s. Participants were instructed to explore the ads freely, as if at home. Next, after an intervening task involving search for detergents, participants were instructed to find and confirm purchase of the target product on the website for shower gels as quickly as possible. The search goal was a specific SKU of Dove shower gel (Dove Calming Night), and the instructions on the screen provided the product name (in neutral white Arial font on a black background) and a verbal description of the product type, but not an image of the package. Participants engaged in a single search

FIGURE 1

EXAMPLE OF AD AND SEARCH DISPLAY IN EYE-TRACKING EXPERIMENT 1

Notes: The superimposed yellow box at the far right of the second row of the search display designates the target product. It was not present in the experiment.

task and pressed "enter" after finding the target product. Next, participants saw a screen with numbers that indicated the locations of the products and responded with the number that they thought corresponded to the target product.

During the ad exposure and the search task, participants' eye movements were recorded with an infrared corneal reflection Tobii T60XL eye-tracker. The eye-tracker registers the point of regard every 17 ms (60 Hz) with a spatial resolution better than 0.4°, by measuring the reflection of infrared rays emitted by the eye-tracker on the cornea (hard outer layer) of both eyes. Eye-fixation positions were computed using the BIT algorithm (van der Lans et al. 2011). Each product in the search display was marked as an Area of Interest (AOI) with standard software. The time in milliseconds that it took to find the target product was recorded for each participant, as the time between the moment that the search display appeared on screen and the moment that participants pressed "enter." To be able to analyze the eye-tracking data, we applied the following exclusion criteria. First, participants with less than 80% valid point-of-regard data (van der Lans and Wedel 2017) were dropped. Second, participants who did not fixate on any of the product images on the website during the search task were excluded. Third, to assure that the instruction of the search task was read, participants who spent less than 1 s on the instruction page were excluded. Fourth, participants with excessively long search times were excluded (natural logarithm of search time >3SDs above sample mean, 28.67 s). Fifty-five participants met the first exclusion criterion (33%), likely because they repeatedly looked at the keyboard during the experiment to prepare for their response (the response task in experiments 2 and 3 addresses this problem). None of the participants met the other three exclusion criteria. This resulted in a sample size of 111 participants with valid data. Including all participants did not qualitatively change the results (see web appendix F).

Analyses

We use Bayesian (multivariate) regression with five dependent variables Y: the time to complete the search task in milliseconds, and the fixation frequencies and durations on, respectively, the target and competitors. Details are in web appendix G. The explanatory variables X are: ad ($X_{c,1}$, 1= 0/1: no ad/ad), product image ($X_{c,2} = -1/0/1$: ad without product image/no ad/ad with product image), color contrast ($X_{c,3} = -1/0/1$: white: high contrast with product image/no ad/blue: low contrast with product

TABLE 1

DESCRIPTIVE STATISTICS—EYE-TRACKING EXPERIMENTS 1–3.

Condition	*N*	Search time (s)	Eye fixations on target		Eye fixations on competitors	
			Frequency (number)	Duration (ms)	Frequency (number)	Duration (ms)
Eye-tracking experiment 1						
No ad	21	6.31 (3.92)	3.14 (1.93)	505 (316)	18.38 (12.16)	222 (47)
Ad	90	6.03 (3.35)	3.67 (2.84)	418 (234)	18.18 (11.91)	224 (60)
Product image	45	4.96 (2.94)	3.36 (2.33)	395 (213)	15.22 (12.30)	213 (64)
No product image	45	7.09 (3.43)	3.98 (3.28)	440 (254)	21.13 (10.86)	235 (53)
Non-contrasting background	46	6.04 (3.08)	4.11 (3.47)	418 (250)	17.96 (10.43)	227 (42)
Contrasting background	44	6.01 (3.65)	3.20 (1.92)	417 (219)	18.41 (13.41)	221 (74)
Overall	111	6.08 (3.45)	3.57 (2.70)	434 (253)	18.22 (11.90)	224 (57)
Eye-tracking experiment 2						
No ad	103	8.92 (7.04)	5.38 (3.62)	279 (115)	31.09 (25.83)	208 (43)
Ad	400	8.65 (6.47)	5.21 (3.12)	283 (138)	29.57 (22.91)	209 (51)
Unorganized website	255	8.57 (6.15)	5.24 (3.27)	276 (126)	29.64 (23.05)	207 (48)
Visually organized website	248	8.85 (6.77)	5.25 (3.19)	289 (142)	30.14 (24.04)	211 (51)
Overall	503	8.71 (6.59)	5.24 (3.23)	282 (134)	29.88 (23.52)	209 (49)
Eye-tracking experiment 3						
No product image	221	7.68 (5.94)	4.43 (3.60)	251 (110)	28.78 (23.74)	198 (48)
Product image	237	4.86 (4.06)	4.43 (3.51)	235 (122)	17.64 (16.31)	178 (38)
Unorganized website	155	6.01 (5.00)	4.17 (3.80)	242 (96)	22.23 (19.13)	185 (47)
Visually organized website	146	6.32 (4.47)	4.25 (3.38)	262 (165)	23.32 (18.51)	196 (44)
Alphabetically organized website	157	6.34 (6.10)	4.85 (3.44)	224 (68)	23.52 (24.64)	181 (40)
Overall	458	6.22 (5.25)	4.43 (3.55)	242 (116)	23.02 (20.97)	187 (44)

Notes: Means, with SDs in parentheses.

image), and the product image × color contrast interaction ($X_{c,4}$). In addition, we investigate the extent to which CCA (M_c) mediates the effects of product image and color contrast on search efficiency by adding it to the explanatory variables in the regression model. The Bayesian estimation algorithm allows us to obtain the (posterior) standard deviations, credible intervals, and (Bayesian) *p*-values of the indirect effects (Zhang, Wedel, and Pieters 2009). Bayesian *p*-values, credible intervals and partial eta-square effect sizes (η^2) are reported. Because the Bayesian partial eta-square accommodates parameter uncertainty, it is typically lower than the traditional measure (Wedel and Dong 2020).

Results and Discussion

Descriptive Statistics. Table 1 contains descriptive statistics of all three eye-tracking experiments. On average, participants in Eye-tracking experiment 1 found the target in 6.08 s (SD = 3.45), with 21.78 fixations (SD = 12.45). Almost all participants (108 of 111) accurately identified the target product. Our results did not change substantively, if we only analyzed the 108 participants who accurately completed the search task (see web appendix H). Average search times do not depend much on whether an ad for the target was present (ad: $M = 6.03$ s; no ad: $M = 6.31$ s). However, average search times strongly depend on whether the ad contains a product image ($M = 4.96$ s) or not ($M = 7.09$ s). Our proposed decomposition of search time into fixation frequencies and durations on, respectively, the target and competitors accounted 91.96% of its variance, with the remaining variance due to saccades, blinks, and the like.

Estimation Results. There was no evidence (table 2) that the mere presence of an ad has an impact on search time, but there was evidence that the product image in the ad reduces search time (-1.07, $p = .002$, $\eta^2 = .073$). The average predicted reduction in search time was 2.14 s, or a 30.1% efficiency gain, compared to the average search time in case of an ad without product image (7.09 s, table 1). As hypothesized, the efficiency gain was due to competitor rejection: the ad reduced the number of fixations (-2.98, $p = .017$, $\eta^2 = .046$) and their durations (-11.49, $p = .056$, $\eta^2 = .028$), on competitors. There was no evidence that faster target acceptance (fixations and their duration on the target) drove faster search.

Mediation Analysis. The effect of the product image on the number of fixations on competitors during target search was mediated by CCA. As reported in table 2, a product image in the ad positively affected CCA (0.09, $p = .042$, $\eta^2 = .032$). Furthermore, CCA negatively affected the number of fixations on competitors (-11.80, $p < .001$, $\eta^2 = .161$). Importantly, the direct effect of the presence of a product image on the number of fixations on competitors became weaker when CCA was added to the model

TABLE 2

ATTTENTION PROCESS ANALYSIS—EYE-TRACKING EXPERIMENT 1.

Model term	Search time	Eye fixations on target				Eye fixations on competitors				Mediator
		Frequency		Duration		Frequency		Duration		Color congruent attention
		1	2	1	2	1	2	1	2	
Intercept	**6.31 (0.74)**	**3.13 (0.59)**	**8.19 (2.15)**	**505.37 (55.44)**	220.75 (206.97)	**18.37 (2.58)**	**−20.66 (8.81)**	**222.21 (12.41)**	**162.33 (46.06)**	**−3.31 (0.09)**
Ad	−0.28 (0.82)	0.52 (0.65)	0.62 (0.64)	−87.73 (61.65)	−93.65 (61.44)	−0.20 (2.87)	−1.02 (2.62)	1.69 (13.80)	0.50 (13.74)	−0.07 (0.10)
Product image in ad	**−1.07 (0.36)**	−0.31 (0.28)	−0.44 (0.28)	−22.56 (26.74)	−15.13 (27.21)	**−2.98 (1.24)**	*−1.95 (1.17)*	*−11.49 (6.02)*	−9.90 (6.12)	**0.09 (0.04)**
Background blue	0.02 (0.36)	0.45 (0.28)	0.43 (0.28)	0.44 (26.58)	2.18 (26.55)	−0.23 (1.24)	−0.02 (1.14)	3.44 (6.00)	3.78 (5.95)	0.02 (0.04)
Product image × background	0.37 (0.36)	−0.15 (0.28)	−0.14 (0.28)	6.44 (26.77)	6.05 (26.77)	1.16 (1.24)	1.08 (1.14)	5.53 (6.03)	5.41 (5.97)	−0.01 (0.04)
Mediation										
Color congruent attention	–	–	**1.53 (0.65)**	–	−85.97 (60.27)	–	**−11.80 (2.57)**	–	−18.17 (13.44)	–
Indirect effects										
Product image → color congruent attention	–	–	*0.12 (0.09)*	–	−6.41 (6.96)	–	**−0.99 (0.57)**	–	−1.33 (1.54)	–

Notes: Posterior medians; bold (italic) indicates that the 95% (90%) credible interval does not cover zero. SDs of posterior estimates are between parentheses. The columns frequency and duration 1 and 2 contain the estimates for (1) direct effects of the experimental conditions on eye fixations and (2) conditional direct effects when the mediator is included.

(estimate for number of fixations: -1.95, $p = .094$, $\eta^2 = .020$). There was evidence for an indirect effect of the product image on the number of competitor fixations via the CCA measure (estimate of indirect effect: -0.99, $p = .042$). There was, however, also an effect of the product image on the number of fixations on the target (estimate: 1.53, $p = .016$, $\eta^2 = .047$), but this effect was almost eight times smaller than its effect on reducing fixations on competitors.

Discussion. The presence of a product image in an ad, and not the mere exposure to an ad, strongly improved search efficiency for that product by reducing the number of fixations, and to a lesser extent by reducing the duration of fixations, on competing products. This effect was mediated by our new measure of CCA, which shows that the product image improves search of the target product predominantly by supporting rejection of competing products on the shopping website, rather than by enhancing the identification of the target. There was no effect of the contrast between product image and background of the ad, and therefore this factor is not investigated further in subsequent experiments. Eye-tracking experiment 2 extends these results by examining the possible moderating effect of the organization of products on the website and assessing the persistence of the ad-induced search benefits across a sequence of search tasks.

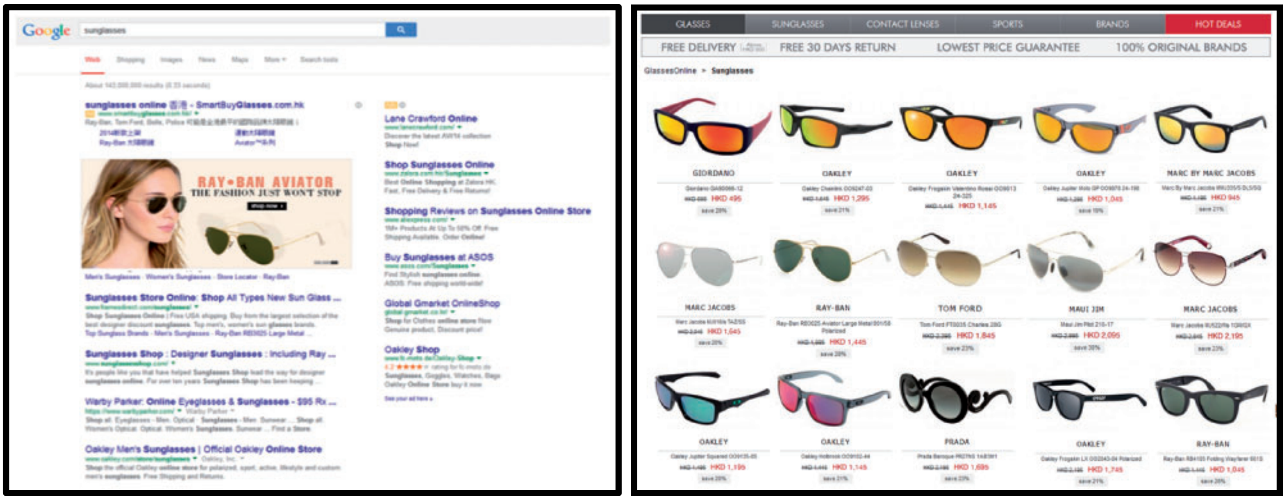
EYE-TRACKING EXPERIMENT 2

Participants and Stimuli

A sample of 130 undergraduate students from a public university (M age = 20) participated for the equivalent of \$8. They saw online ads embedded in the context of search engine websites. Each participant viewed four randomly selected (out of 10) online search ads for four different product categories. In view of experiment 1's findings, all ads contained a product image. Next, each participant searched for five different products (out of 10) on each of five different shopping websites (cameras, fragrances, shoes, sunglasses, and watches; see figure 2 for an example of an ad and a website, and web appendix I for all ads and websites). Four out of these five products were presented earlier in the four ads a participant was exposed to. Thus, there was one condition where participants had not seen an ad for any of the products. Participants first saw all four online ads and then conducted the five searches to create temporal separation between the exposure and the search task. Presentation order of the ads and websites was counterbalanced. Participants were randomly assigned to either search engine results of Google or of Microsoft Bing, both containing an ad. We included these two contexts for generalizability, but our analyses revealed that the type of search engine did not affect any of the results, and we do not discuss these differences further. Also, for

FIGURE 2

SAMPLE GOOGLE AD AND ORGANIZED WEBSITE IN EYE-TRACKING EXPERIMENT 2



Notes: Shape and color were the organizing principles of the shopping website: glasses in each row have similar colors and shapes.

generalizability, each category was represented by two different websites that were adapted from real shopping websites. For each category, the two shopping websites contained two target products (Cameras: Pentax Q and Fuji Finepix X100S; Fragrances: Jimmy Choo and Dolce&Gabbana-The One Desire; Shoes: Asics Gel-Kayano 20 and Salomon S-Lab Sense 3 Ultra; Sunglasses: Ray-Ban Aviator and Oakley Frogskin Valentino Rossi; Watches: G-Shock GW-3500B-1AER and Seiko Sportura Kinetic GMT). On the shopping websites, the products were presented either unorganized or organized horizontally based on color or shape similarity.

Tasks, Measures, and Analyses

Data collection procedures, instructions, ad exposure duration, and response-time and eye-tracking measures were similar to those in eye-tracking experiment 1, with a few exceptions. Here, participants were individually seated in front of 24-inch LCD computer screens (1200 × 1920) and were exposed to four randomly selected ads, shown in random order. After viewing the four online search engine results, participants were asked in a seemingly unrelated task to buy specific products for a friend from an online shopping website. The first task from an unrelated category (mobile phones) served to familiarize participants with the procedure. Next, participants saw five different shopping websites. Participants were instructed to find and buy a specific target product as quickly as possible on each of the sites, based on a verbal description of the product, and to click on the target product to buy it as soon as they had found it. The exclusion criteria resulted in a final dataset containing 503 searches across 121 participants, excluding 147 search tasks. Of the excluded searches, 92 had insufficient eye-tracking data (<80%), 39 did not have any eye fixations on any of the product images, instructions were not read 13 times, and 3 search times exceeded 50.70 s (i.e., 3× SD > M). The more natural use of mouse clicks (rather than the space bar in eye-tracking experiment 1) improved eye-tracking data quality. It also led to a few participants accidentally double-clicking on the page prior to the instructions, resulting in this page being skipped, because of which 13 search tasks had to be excluded. Our proposed decomposition of search time into fixation frequencies and durations on, respectively, the target and competitors accounted for 96.64% of the variance in search times.

A Bayesian multivariate regression model similar to that in eye-tracking experiment 1 was used for data analysis, but with an added random individual-specific intercept to accommodate the multiple stimuli and tasks. The vector of explanatory variables $X_{c,t}$ for consumer c and search task t includes dummy variables representing the within-participant manipulations: ad ($X_{c,t,1} = 0/1$ t,1=0/1: no ad/ad), shopping website organization ($X_{c,t,2} = 0/1$ t,2=0/1: unorganized/organized), and the ad × shopping website organization interaction ($X_{c,t,3}$). To investigate the persistence of online advertising effects across search tasks, we included (mean-centered) search sequence ($X_{c,t,4}$ ranging from −2 to 2) as well as its interaction with the ad ($X_{c,t,5}$). Finally, we controlled for category-specific fixed effects and the interaction between search sequence and organization of the shopping website.

TABLE 3

ATTENTION PROCESS ANALYSIS—EYE-TRACKING EXPERIMENT 2.

	Search time	Eye fixations on target				Eye fixations on competitors				Mediator
		Frequency		Duration		Frequency		Duration		Color congruent
Model term		1	2	1	2	1	2	1	2	Attention
Intercept	**15.85 (0.98)**	**6.13 (0.50)**	**7.08 (0.63)**	**304.11 (20.75)**	**304.59 (26.16)**	**51.69 (3.67)**	**39.49 (4.60)**	**238.90 (6.42)**	**251.11 (7.98)**	**−2.34 (0.14)**
Ad	**−2.34 (0.93)**	−0.62 (0.47)	−0.65 (0.46)	0.01 (19.11)	−0.21 (19.12)	**−7.66 (3.48)**	**−7.32 (3.39)**	1.58 (5.61)	1.36 (5.55)	0.07 (0.13)
Website (organized)	**−2.45 (1.20)**	−0.77 (0.61)	−0.83 (0.61)	8.33 (24.97)	8.57 (25.02)	−7.05 (4.50)	−6.10 (4.41)	4.68 (7.45)	4.07 (7.31)	0.18 (0.16)
Ad × website	**3.74 (1.34)**	1.01 (0.69)	1.02 (0.68)	5.07 (28.11)	5.02 (28.13)	**10.58 (5.06)**	**10.27 (4.94)**	−1.43 (8.42)	−1.40 (8.29)	−0.07 (0.18)
Search sequence	−0.73 (0.47)	−0.20 (0.24)	−0.25 (0.24)	7.61 (9.84)	7.30 (9.83)	*−3.10 (1.77)*	−2.47 (1.75)	4.64 (2.94)	3.96 (2.91)	*0.12 (0.06)*
Ad × search sequence	*0.83 (0.48)*	0.37 (0.24)	*0.45 (0.25)*	−9.28 (10.09)	−9.03 (10.18)	**3.62 (1.82)**	2.74 (1.80)	−2.80 (3.02)	−1.86 (3.02)	**−0.17 (0.07)**
Website × search sequence	−0.11 (0.37)	−0.02 (0.19)	−0.01 (0.19)	−3.38 (7.69)	−3.29 (7.69)	−0.84 (1.39)	−0.96 (1.37)	0.30 (2.28)	0.39 (2.26)	−0.02 (0.12)
Mediation										
Color congruent attention	–	–	**0.40 (0.17)**	–	0.16 (6.91)	–	**−5.22 (1.22)**	–	**4.69 (2.04)**	–
Indirect effects										
Search sequence → color congruent attention	–	–	*0.04 (0.03)*	–	0.01 (0.94)	–	*−0.60 (0.37)*	–	*0.57 (0.44)*	–
Ad × search sequence → color congruent attention	–	–	**−0.06 (0.04)**	–	−0.02 (1.24)	–	**0.84 (0.41)**	–	**−0.81 (0.50)**	–

Notes: Posterior medians; bold (italic) indicates that the 95% (90%) CI does not cover zero. SDs of posterior estimates are between parentheses. The columns frequency and duration 1 and 2 contain the estimates for, respectively, (1) direct effects of the experimental conditions on eye fixations, and (2) conditional direct effects when the mediator is included.

Results and Discussion

Descriptive Statistics. Table 1 contains the descriptive statistics. On average, participants searched 8.71 s (SD = 6.59) and made 35.12 fixations (SD = 24.12). Search accuracy was 91.3%. Analyses with only participants who accurately completed the search task did not change the main findings qualitatively (see web appendix H). Average search time after ad exposure was slightly shorter than without exposure (ad: $M = 8.65$ vs. no ad: $M = 8.92$). On the websites organized by perceptual features, search times were slightly longer (unorganized: $M = 8.57$ vs. organized: $M = 8.85$).

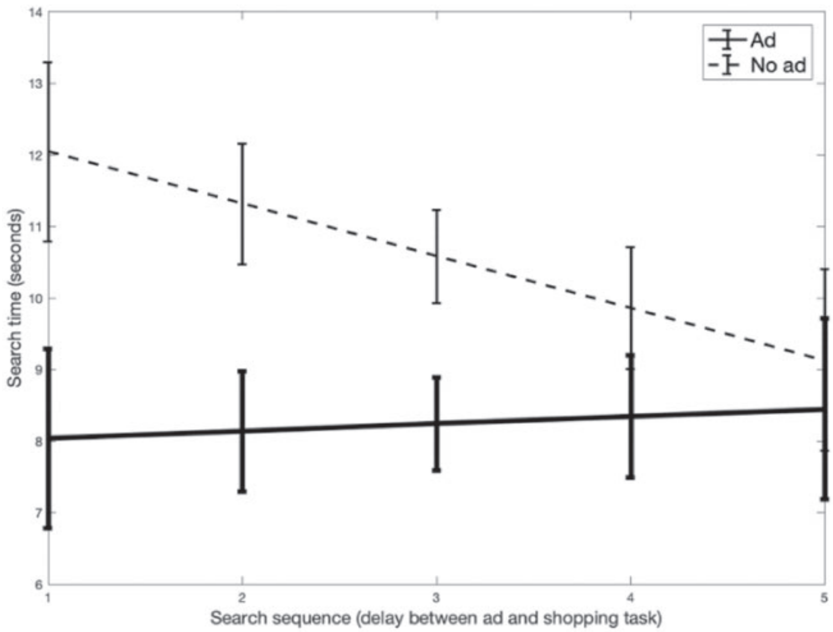
Estimation Results. Table 3 summarizes the results. The presence of the ad reduced search time (−2.34, $p = .011$, $\eta^2 = .024$), and somewhat more so for searches shortly after ad exposure (ad × search sequence: 0.83, $p = .079$, $\eta^2 = .030$). Figure 3 illustrates the ads' effects on search time. Advertising was highly effective in the first search after ad exposure, reducing search time on average by 4.00 s ($p = .001$). This amounted to a 33.2% reduction in search time, which is highly consistent with eye-tracking experiment 1 despite the different stimuli, search tasks, and participant samples. On the final search, when the delay between exposure and search was larger, search-time reduction waned to 0.68 s ($p = .624$).

Shopping websites organized horizontally by perceptual features resulted in shorter search times (−2.45, $p = .041$, $\eta^2 = .041$). The ad × shopping website interaction (3.74, $p = .005$, $\eta^2 = .088$) showed that the ads were less effective in reducing search time for organized shopping websites. Exposure to an ad before an unorganized shopping website made search for the target product more efficient. This advertising effect was due to a reduced number of fixations on the competitors (−7.66, $p = .028$, $\eta^2 = .019$), especially when search occurred shortly after viewing the ad (search sequence × order: 3.62, $p = .046$, $\eta^2 = .042$). The main effect of search sequence indicated a weak reduction in the number of fixations on competitors over time (−3.10, $p = .080$, $\eta^2 = .039$). On the other hand, in visually organized websites, ad exposure led to a higher number of fixations on competitors (10.58, $p = .036$, $\eta^2 = .053$). We did not observe effects on the duration of competitor fixations and there was no evidence for an effect of the experimental conditions on number and duration of fixations on the target.

Mediation Analysis. As hypothesized, the ads influenced CCA (table 3): shortly after ad exposure, participants suppressed features of competitor products (interaction ad × search sequence: −0.17, $p = .012$, $\eta^2 = .066$). When participants gained experience with the task, they suppressed competitors' features even more (search sequence: 0.12, $p = .061$, $\eta^2 = .043$). However, the design of the shopping website did not influence the suppression or

FIGURE 3

SEARCH TIME AS FUNCTION OF SEARCH SEQUENCE—EYE-TRACKING EXPERIMENT 2.



Notes: For the graph, all other variables were set to their mean values. Vertical lines indicate 95% CI.

enhancement of features. Also, as hypothesized, CCA reduced the number of fixations on competitors (−5.22, $p < .001$, $\eta^2 = .043$). In further support of our theory, the ad × search sequence interaction on competitor fixations disappeared after controlling for CCA (2.74, $p = .125$, $\eta^2 = .025$), as did the main effect of search sequence (−2.47, $p = .161$, $\eta^2 = .025$). The interaction between ad and search sequence (0.84, $p = .010$) and search sequence (−0.60, $p = .061$) influenced competitor fixations indirectly via their effect on CCA. There was also an indirect effect of the ad × search sequence interaction, through CCA, on fixation durations on competitors (indirect effect: −0.81, $p = .020$).

Discussion and Follow-Up Studies. Eye-tracking experiment 2 documented once more how prior ad exposure can help suppressing the features of competitors' products during subsequent search. Such competitor suppression improved search efficiency for the target. Importantly, this experiment showed that these ad effects dissipated when more than three other search tasks intervened between ad exposure and target search. We also found evidence that organizing the products on the shopping website horizontally by visual features improved search efficiency overall, but that it eliminated the efficiency gains due to ad exposure. This demonstrates the importance of the interaction between top-down (ad exposure) effects and bottom-up (website organization) factors in product search.

We conducted eye-tracking experiment 3 to delve deeper into these findings, manipulating the presence of a product image in the ad, looking at two other ways to group the products on the shopping site, and incentivizing participants (details are in web appendix J). Descriptive statistics of this experiment are provided in table 1, based on 458 search tasks across 166 participants that saw ads with or without a product image, and searched on shopping sites for fragrances, running shoes, and sunglasses, similar to eye-tracking experiment 2. Participants in this experiment were incentivized to find the target as fast as possible. Clicking on the online ad directly brought participants to a shopping website. Extending eye-tracking experiment 2, the website was organized vertically (rather than horizontally) based on perceptual features, or alphabetically according to the names of the products. This allowed us to test, first, whether the direction of organization of products (Shi et al. 2013) matters for the moderating effect of website organization, and, second, to investigate whether in absence of a product image, search is slower.

Eye-tracking experiment 3 replicated the effect of exposure to ads with a product image on product search: the presence of a product image in the ad reduced search time (−2.13, $p = .025$, $\eta^2 = .052$; efficiency gain is 27.7%), due to the reduced number of fixations on competitors (−5.12, $p = .006$, $\eta^2 = .053$).

Alphabetical website organization increased fixations on the target (2.40, $p < .001$, $\eta^2 = .112$). For alphabetically organized websites, the presence of a product image in the ad reduced fixations on the target (−2.37, $p = .005$, $\eta^2 = .070$), but not on competitors. Thus, in the absence of the product image in the ad, participants fixated more on the target but not on competitors, which suggests that they rely more on reading the target brand name (and other detailed but slower processes). However, this finding makes systematic reading of all brand names an unlikely explanation for less efficient search in the case that there is no product image in the ad. Alphabetical organization did not affect search time, nor did it moderate the effects of the ad on search time. Furthermore, we did not find a moderating effect of the predominantly vertical (column-wise) organization of the website. As shown n figure 2 in web appendix K, the vertical distance between products in the shopping website is larger compared to the horizontal distance, which may hamper perceptual grouping (Wagemans et al. 2012). In addition, the direction of eye movements primed by a product display may be primarily horizontal (Shi et al. 2013), due to which vertical grouping may be less effective. Taken together, eye-tracking experiment 3 showed that the benefits of exposure to an online ad with a product image accrue for alphabetically and vertically organized shopping sites to the same extent as they do for randomly organized websites.

Overall, the three eye-tracking experiments revealed that online ads with an image of the advertised product reduced search time by about 30% on cluttered (unorganized) websites, as well as on websites that are vertically or alphabetically organized. A decomposition of the search process showed that this gain in search efficiency is primarily driven by a reduced number of fixations on competing products after seeing the ad. Furthermore, mediation analyses showed that competing products that are perceptually different from the target based on color are suppressed and receive fewer fixations and that this accounts for the efficiency gain in search.

These findings are not self-evident to participants as shown in a follow-up, pre-registered, lay-theory experiment (details in web appendix L). In that study, participants were asked to predict the effects of two online ads, one with and one without a product image. The study had a two-group design: dissimilar versus similar competing products on the website. A majority of participants (56.7%, 131 out of 231) predicted that a product image in an ad would not improve search efficiency. Importantly, participants' predictions of the effect of the ad were the same across shopping website conditions ($p = 1.00$). Moreover, analysis of open-ended responses showed that participants who predicted that an ad with product image would reduce search time, mostly provided faster target acceptance as the main explanation (71%), while none of the participants mentioned faster rejection of competitors as an explanation. All three eye-tracking experiments revealed that the opposite of these lay theories holds true.

Two search-time experiments further tested our hypothesis and aimed to replicate the findings in larger and different samples of participants, exposure contexts of higher ecological validity, tasks in which participants were incentivized to find a product of their own choice, while manipulating rather than measuring color congruency, using pre-registered procedures.

SEARCH-TIME EXPERIMENT 1

Using a pre-registered,[2] incentivized task, search-time experiment 1 tested the hypothesis that online ads improve search efficiency on shopping websites, when competitors are visually distinct from the target (high versus low color congruency). Furthermore, this experiment broadened the scope of the theory by allowing participants (1) to search for an advertised product that they choose themselves, instead of searching for a pre-determined target product for a friend, (2) to process the ad at their own pace, instead of after a fixed viewing time of 10 s, and by (3) including a larger and more representative sample of participants in a context with even higher ecological validity.

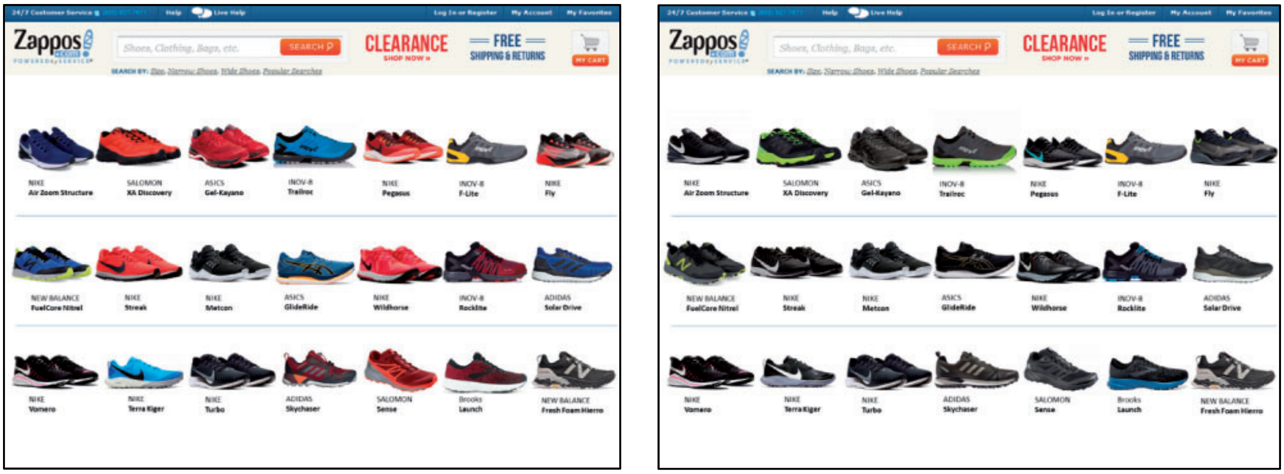
Participants and Stimuli

A sample of 800 members (we recruited 801, but 1 participant did not complete the task) from Amazon's MTurk panel participated in our study in exchange for $1 and a 2 percent chance to win the product of their choice. Sample size estimation was based on a power calculation for a significance level of .05 and a power of .80. Expected effect sizes were calculated based on the cell means and standard deviations obtained in eye-tracking experiment 3, while accounting for their uncertainty and an expected exclusion of about 25% of the participants (Anderson, Kelley, and Maxwell 2017). Each participant was randomly assigned to one of four conditions of a 2 (ad design: without or with product image) × 2 (color congruency of the website: high with visually similar products based on color, or low) design. Websites were manipulated such that the Euclidean distance of CIELAB measures between competitors and the target products were substantially smaller in the high congruency condition as compared to the low congruency condition. Thus, rather than using the measured Euclidian distance of CIELAB values in calculating the color congruency mediator as was done in the eye-tracking experiments, to establish causality of its effect we manipulated it (figure 4 shows an example).

2 https://aspredicted.org/blind.php?x=xw6sp9.

FIGURE 4

SAMPLE SHOPPING WEBSITES IN SEARCH-TIME EXPERIMENT 1



Notes: The left-hand side contains a website with low color congruency, while the right-hand side contains a website of high color congruency with products that are similar to the chosen product (New Balance Foam Hierro, located in the bottom-right of the websites).

After a training task (for cameras), participants in each condition performed three online shopping tasks for different categories (running shoes, fragrances, and sunglasses). At the start of each shopping task, participants first chose their favorite product among four alternatives. To incentivize their choice, participants were informed that they had a two percent chance of winning their chosen item. Next, participants were presented with a screenshot of a real website (ESPN, MSN, or New York Times, counterbalanced across the three shopping tasks) in which we replaced an ad with an online ad for the product of their choice, which they could explore as long as they wanted. After clicking on the online ad, participants arrived on the shopping website that contained their chosen product (all ads and shopping websites are in web appendix M). Presentation order of the product categories was counterbalanced, and we randomized the location of the chosen product across four positions on the shopping website.

Tasks, Measures, and Analyses

The shopping tasks were programmed in Qualtrics software, and all participants performed them on their laptop or desktop in a location of their choice. At the start of each shopping task, participants were asked to imagine that they were looking for a new product from a specific category, and that they had narrowed down their decision to four alternatives. Next, they were instructed to indicate their preferred alternative among the set of four products. For the three categories, the four alternatives were Asics Gel-Kayano, Nike Air Zoom Structure, New Balance Foam Hierro, and Salomon Sense (Running Shoes); Gucci by Gucci, Estée Lauder Spellbound, D&G The One Desire, and Jimmy Choo The Original Fragrance (Fragrances); and Prada Linea Rossa, Ray-Ban Aviator, Marc Jacobs, and Oakley Frogskin (Sunglasses).

After choosing their preferred product, participants saw a website (ESPN, MSN, or New York Times) with an ad of their preferred product inserted at the position where these websites originally presented an actual ad. Participants could look at the website and ad as long as they wished, before clicking on the ad to proceed to the shopping website. Before arriving on the shopping website, they were presented a black screen with a white cross in the center for 1 s to assure that their first eye fixation was in the middle of the shopping website. On the shopping website, participants were instructed to find their chosen product as fast as possible by clicking on it. To incentivize participants, they were informed that they had a chance of 1 in 50 to win their preferred product if they were among the participants who correctly found their chosen product the fastest. To implement this incentive scheme, we followed Saint Clair and Forehand (2020, p. 1022) and informed participants that we would contact them through the MTurk messaging system to arrange shipment, which we did. After finishing the three shopping tasks, participants answered five multiple choice questions: (1) whether they shopped online in the past 6 months (yes/no) and their (2) familiarity with each of the three categories (5-point: not familiar at all to extremely familiar), (3) overall opinion about the study (four 5-point items: very easy/very difficult, boring/interesting, pleasant to do/unpleasant to do, difficult to read/

TABLE 4

DESCRIPTIVE STATISTICS—SEARCH-TIME EXPERIMENT 1.

	Overall	Low color congruency website		High color congruency website	
		Product image	No product image	Product image	No product image
Search time (s)	8.81 (9.36)	8.26 (9.18)	9.52 (9.79)	9.07 (10.23)	8.29 (8.01)
Time on website with ad (s)	3.84 (4.60)	4.05 (5.02)	3.50 (4.05)	4.83 (5.18)	2.98 (3.83)
N	1,774	393	456	470	455

Notes: Means, with SDs between parentheses.

easy to read), (4) age (10 years intervals from younger than 20 years to older than 60 years), and (5) gender. Optionally, participants could add open comments.

We removed participants and tasks using the following pre-registered exclusion criteria. First, we removed 113 participants who found none of their chosen products in the three shopping tasks. Second, we removed 72 participants who spent less than 3 s on the page with general instructions.[3] Third, we excluded four more participants who mentioned in the open comments that they had reduced vision and could not clearly see the stimuli. Fourth, similar to the eye-tracking experiments, we removed 59 shopping tasks for which participants spent excessively long or short times (±3 SD of the mean of log search time on either the website with the ad or on the shopping website). The final sample consisted of 1,774 valid shopping tasks across 611 participants.

We used a Bayesian multilevel regression model similar to that in eye-tracking experiments 2 and 3 to investigate the effect of the experimental manipulations on log search time. The explanatory variables include dummy variables representing the between-participant manipulations: product image ($X_{c,1} = 0/1{=}0/1$: no product image/product image), website color congruency ($X_{c,2} = 0{=}0/1$: high/low), and the product image × website heterogeneity interaction ($X_{c,3}$), the sequence in which the shopping task appeared ($X_{c,t,4}$), as well as the interactions of sequence with product image and website color congruency ($X_{c,t,5}$, $X_{c,t,6}$, respectively). Finally, we included a set of control variables (category-specific fixed effects, gender, age, and the log time that the participant viewed the website with the ad).

Results and Discussion

Descriptive Statistics. Table 4 provides descriptive statistics. On average, participants in this study (53.7% males) searched 8.81 s (SD = 9.36), which is very similar to the average search times in eye-tracking experiment 2. The longer search times compared to those in the (incentivized) eye-tracking experiment 3 may be due to a combination of the higher age of participants here (median in the 30–39 years category, with 7.5% being 60 years or older) (Ball et al. 1988), the designs of the shopping websites, and the fact that participants searched for a product of their own choice. Search accuracy was comparable to eye-tracking experiment 3 and equaled 84.5% (results did not change qualitatively when including only accurate searches in the analysis: see web appendix O). As in all previous studies, average search times were shorter when participants were exposed to an ad with a product image ($M = 8.70$ s vs. no product image: $M = 8.91$ s), especially before searching on a website low in color congruency ($M = 8.26$ s vs. high: $M = 9.52$ s).

TABLE 5

ESTIMATION RESULTS—SEARCH-TIME EXPERIMENT 1.

	Ln(search time)
Intercept	**1.51 (0.12)**
Product image	**−0.29 (0.11)**
Low congruency website	0.01 (0.10)
Product image × low congruency website	**0.22 (0.09)**
Sequence	−0.01 (0.04)
Sequence × product image	0.01 (0.04)
Sequence × low congruency website	−0.05 (0.04)
Gender	0.04 (0.05)
Age	*0.04 (0.02)*
Ln(time Google)	**0.15 (0.03)**

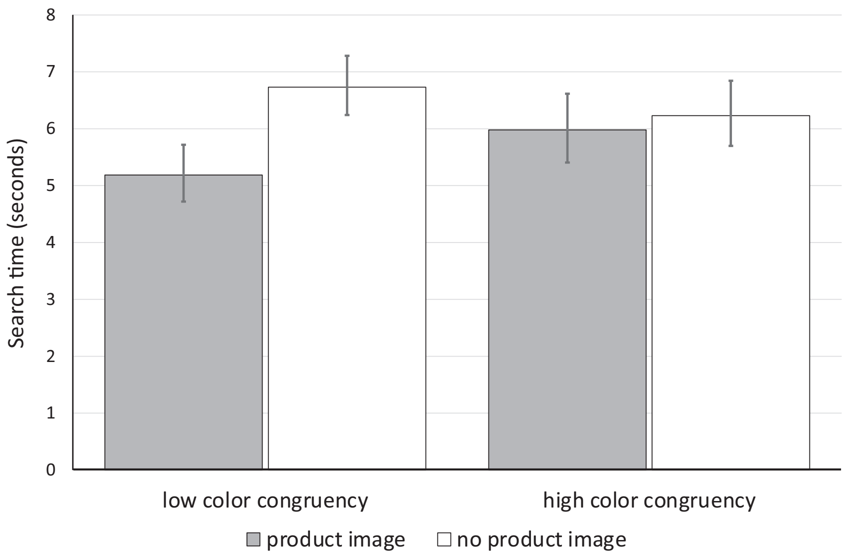
Notes: Posterior medians; bold (italic) indicates that the 95% (90%) CI does not cover zero. SDs of posterior estimates are between parentheses.

Estimation Results. Table 5 presents the parameter estimates. The presence of a product image in the ad reduced search time (−0.29, $p = .007$, $\eta^2 = .040$). Consistent with the results from the eye-tracking experiments, a product image only reduced search time when the website contains competitors that are visually dissimilar (low color congruency), which is reflected in the positive product image × color congruency interaction (0.22, $p = .021$, $\eta^2 = .018$). Figure 5 depicts this interaction effect. A product

3 Compared to the more controlled eye-tracking experiments 1–3, we used 3 s instead of 1 s. It took over 3 s to read the instructions, and more than 1 s to skip through the instruction page without reading (only one participant spent less than 1 s on this page). Follow-up analyses in web appendix N show that our results are robust for other cutoffs (1 and 10 s).

FIGURE 5

MEDIAN POSTERIOR SEARCH TIMES ACROSS CONDITIONS—SEARCH-TIME EXPERIMENT 1



Notes: The vertical lines correspond to 95 percent posterior intervals. To compute the bars from the model estimates, all other (control) variables were set to their sample averages.

image reduced search times by 22.9% ($p < .001$) on low color congruency websites and did not affect search times on high color congruency websites where competitors were similar to the target ($p = .518$). Older participants tended to require more time to find the target (0.04, $p < .062$, $\eta^2 = .003$). People who spent more time viewing the ad also needed more time to find the target brand (0.15, $p < .001$, $\eta^2 = .033$), probably because they generally spend more time on the entire task ($r = 0.33$, $p < .001$). Together, these findings demonstrate again that product images in advertising lead to search efficiency gains on websites that lack a systematic organization of products in terms of their visual features, even when consumers were free to watch the ad at their own pace and click on the product they had chosen themselves.

Discussion and Replication Study. In sum, search-time experiment 1 confirmed our hypothesis that online advertising reduces search time, but only on shopping websites where competitors are visually distinct from the target. The results further supported the hypothesis that online advertising facilitates top-down modulation by suppressing competitors. The findings were obtained in an incentivized, experimental context with high ecological validity because of self-paced exposure to ads inserted in websites as they occurred on the web, and participants searching for a product of their own choice.

These results were replicated in incentivized search-time experiment 2 ($n = 808$), with online ads that were embedded in Google search results similar to eye-tracking experiment 3. The presence of a product image in the ad reduced search time ($p = .028$; search efficiency gain is 24.0%), but only for low color congruency websites with dissimilar competitors ($p = .043$). Web appendix P provides the details.

CONCLUSION

Ninety percent of consumers report having searched for a product on a website after having clicked an online ad, and about one-third report that this happens frequently to them (web appendix A). Yet, little is known about how online advertising can help consumers to implement their purchase plans, and under what conditions and through which processes this takes place. The majority of consumers believe that online ads do not help them find the product that they are searching for, and believe that even if ads would help, that the design of the shopping website plays no role in this (web appendix L). Three controlled eye-tracking experiments and two search-time experiments provide convergent evidence against these lay beliefs and in support of our hypothesis. They showed that online ads that contain an image of the advertised product reduce the subsequent time to search the product on cluttered websites by about 25%, and that these benefits persist for up to three consecutive searches in a web-browsing session. These results are new, and they reveal how advertisers can help consumers to implement their prior intentions at the point-of-purchase. Using eye-tracking analyses and a new measure of CCA, we revealed that the attentional suppression of visual features of competitors was the key process leading to these search benefits of online ads.

Our new measure of CCA relies on standard image processing tools, which adds to its applicability in future academic research and for managerial analytics. CCA can be used for research into the effectiveness of advertising and website, product and package design, especially when interest focuses on top-down influences. Nonetheless, it is a limitation that this measure does not yet capture which specific color features drive similarity. Future research could separately code color channels and other features, such as shape, size, and direction of edges, and condense those in similar attention metrics.

We found that online ads improve search efficiency by enabling a faster rejection of competing products rather than by a faster acceptance of the target product. In addition, the analyses revealed that attention to basic perceptual features of products, enhanced by the online ads, plays a pivotal role in the search process, and helps consumers to suppress competitors' features. These effects were obtained across three eye-tracking and two search-time studies, with a variety of products, categories, and tasks. The generalization emerging from these five experiments is that online ads have little or no effect on search efficiency when on shopping sites the visual contrast between the target and competitors is low, even if that occurs only in a local region of a shopping site. A critical finding is that an ad with a product image enhances the contrast between target and competitors top-down, which makes it easier to reject competing products that are dissimilar from the target. We found that effect for websites with various types of organization, but not websites that are organized horizontally based on visual features. Thus, advertising, product and website design interact in ways that are important to understand for managers. The results of our studies were not premeditated by regular consumers, a majority of whom predicted in a lay-beliefs study that a product image in an ad would <u>not</u> improve search efficiency, irrespective of the organization of the website, while none of them predicted that the product image would help consumers reject competitors faster.

Our findings have implications for consumers and for the management of online advertising. First, this research demonstrates how online advertising can be tailored to help consumers implement their decisions faster and more accurately on cluttered shopping and comparison websites by rejecting competing products more efficiently. Thus, targeted online advertising reinforces a prior intention or decision, and may protect consumers against making impulse purchase decisions by limiting the ability of competing brands to intrude. The reinforcement of prior consideration or intentions is common in behavioral retargeting via ad networks, where based on cookie-tracking technology consumers are shown a clickable ad with an image of a product that they previously considered.

Second, our findings have implications for advertisers. Because search benefits only occur shortly after consumers are being exposed to online advertising, it is important to reach consumers close (within at most three searches) to the moment that they enter a shopping or comparison website. These findings have implications for attribution models used to monetize online advertising. Our results suggest that "costs per impression" is a useful attribution mechanism when impressions are close to the shopping experience, but much less so when the delay between the impression and the targeted behavior is much longer. Proximal ads may not persuade consumers to consider and buy a particular product, but instead may "guide consumers" toward successful implementation of their prior intentions. Furthermore, our research sheds light on the debate whether online ads should be specific (display the product) or generic (presenting a brand logo and category characteristics) (Lambrecht and Tucker 2013). Our findings demonstrate that generic online advertising is ineffective in generating short-term search benefits. Targeting with specific ads that contain a product image shields the focal brand from the competition on shopping websites with multiple products, forming a "perceptual funnel towards the target brand." It is of interest that future research investigates the cost-benefit tradeoffs of these different types of advertising, which the present study has not done, for instance by assessing whether click-through rates differ for ads with or without product images.

The effects of online advertising established in this research occurred in the few seconds that consumers spent searching for a product on online shopping websites, shortly after being exposed to a targeted online ad. Such situations are common in practice when consumers click on ads (see web appendix B). Still, consumers may also use a search engine or price comparison website to find the advertised product. Interestingly, search results on these websites often look quite similar to the shopping websites that we used in our experiments (Shi et al. 2013), as illustrated in web appendix Q which displays Google's search results for a pair of sneakers. We, therefore, believe that our findings also speak to such situations. Relatedly, Du, Xu, and Wilbur (2019) showed that consumers often perform an online search for a product directly after exposure to a TV ad, and we expect our results to also generalize to such situations.

In view of the relatively high search accuracies in our eye-tracking experiments, we did not investigate whether ads affect search accuracy or the inclination to abandon planned purchases. Furthermore, online advertising may also have other short-term effects, for example. by priming and influencing (unplanned) choice on shopping websites. We believe that these are important questions for future research, and hope that our experiments and findings help to stimulate this follow-up work.

To return to the original impetus of this research, we found consistent evidence that prior exposure to online ads that contain a product image speeds up search for the advertised product on shopping websites by suppressing perceptual features of competing products rather than by enhancing perceptual features of the target product. This benefit primarily accrues on websites that lack a systematic organization of products in terms of their visual features. Therefore, the research shows how online ads can support consumers in making planned purchases, which should be of interest to consumers, researchers, and advertisers.

DATA COLLECTION INFORMATION

The first author supervised the collection of data for the first eye-tracking experiment by a research assistant at the Behavioral Lab of the Rotterdam School of Management, Erasmus University, in fall 2007. The first author also supervised the data collection of the second and third eye-tracking experiments by a research assistant at the Behavioral Lab of Hong Kong University of Science and Technology in, respectively, fall 2014 and spring 2017. The first author collected the data for the two Search-Time experiments in February and November 2020 using the online panel of Amazon MTurk. Finally, the first author also collected the data on MTurk for the Consumer Survey (September 2020) and Lay Theory Study (October 2020). The first author analyzed the data for all studies. All data are currently stored in a Dropbox folder under the management of the first author.

REFERENCES

Anderson, Samantha F., Ken Kelley, and Scott E. Maxwell (2017), "Sample-Size Planning for More Accurate Statistical Power: A Method Adjusting Sample Effect Sizes for Publication Bias and Uncertainty," *Psychological Science*, 28 (11), 1547–62.

Arita, Jason T., Nancy B. Carlisle, and Geoffrey F. Woodman (2012), "Templates for Rejection: Configuring Attention to Ignore Task-Irrelevant Features," *Journal of Experimental Psychology. Human Perception and Performance*, 38 (3), 580–4.

Bacon, William F., and Howard E. Egeth (1994), "Overriding Stimulus-Driven Attentional Capture," *Perception & Psychophysics*, 55 (5), 485–96.

Ball, Karlene K., Bettina L. Beard, Daniel L. Roenker, Richard L. Miller, and David S. Griggs (1988), "Age and Visual Search: Expanding the Useful Field of View," *Journal of the Optical Society of America A: Optics and Image Science*, 5 (12), 2210–9.

Baumgartner, Hans, and Pieters Rik (2008), "Goal-Directed Consumer Behavior: Motivation, Volition, and Affect," in *Handbook of Consumer Psychology*, ed. Curtis P. Haugtvedt, Paul M. Herr, and Frank R. Kardes. New York: Psychology Press, 367–92.

Becker, Stefanie I. (2011), "Determinants of Dwell Time in Visual Search: Similarity or Perceptual Difficulty?," *PLoS One*, 6 (3), e17740–5.

Becker, Stefanie I., and Gernot Horstmann (2009), "A Feature-Weighting account of Priming in Conjunction Search," *Attention, Perception, & Psychophysics*, 71 (2), 258–72.

Breuer, Ralph, and Malte Brettel (2012), "Short- and Long-Term Effects of Online Advertising: Differences between New and Existing Customers," *Journal of Interactive Marketing*, 26 (3), 155–66.

Caputo, Giovanni, and Sergio Guerra (1998), "Attentional Selection by Distractor Suppression," *Vision Research*, 38 (5), 669–89.

Chae, Inyoung, Hernán A. Bruno, and Fred Feinberg (2019), "Wearout or Weariness? Measuring Potential Negative Consequences of Online Ad Volume and Placement on Website Visits," *Journal of Marketing Research*, 56 (1), 57–75.

Chatterjee, Patrali, Donna L. Hoffman, and Thomas P. Novak (2003), "Modeling the Clickstream: Implications for Web-Based Advertising Efforts," *Marketing Science*, 22 (4), 520–41.

Cho, Chang-Hoan, and Hongsik John Cheon (2004), "Why Do People Avoid Advertising on the Internet," *Journal of Advertising*, 33 (4), 89–97.

Connolly, C., and T. Fleiss (1997), "A Study of Efficiency and Accuracy in the Transformation from RGB to CIELAB Color Space," *IEEE Transactions on Image Processing: A Publication of the Ieee Signal Processing Society*, 6 (7), 1046–8.

Drèze, Xavier, and François-Xavier Hussherr (2003), "Internet Advertising: Is Anybody Watching?," *Journal of Interactive Marketing*, 17 (4), 8–23.

Du, Rex Yuxing, Linli Xu, and Kenneth C. Wilbur (2019), "Immediate Responses of Online Brand Search and Price Search to TV Ads," *Journal of Marketing*, 83 (4), 81–100.

Duncan, John, and Glyn W. Humphreys (1989), "Visual Search and Stimulus Similarity," *Psychological Review*, 96 (3), 433–58.

Duncan, John, Glyn Humphreys, and Robert Ward (1997), "Competitive Brain Activity in Visual Attention," *Current Opinion in Neurobiology*, 7 (2), 255–61.

Folk, Charles L., Roger W. Remington, and James C. Johnston (1992), "Involuntary Covert Orienting Is Contingent on Attentional Control Settings," *Journal of Experimental Psychology: Human Perception and Performance*, 18 (4), 1030–44.

Försch, Steffen, and Evert de Haan (2018), "Targeting Online Display Ads: Choosing Their Frequency and Spacing," *International Journal of Research in Marketing*, 35 (4), 661–72.

Gaspelin, Nicholas, and Steven J. Luck (2018), "Distinguishing among Potential Mechanisms of Singleton Suppression," *Journal of Experimental Psychology. Human Perception and Performance*, 44 (4), 626–44.

Geyer, Thomas, Hermann J. Müller, and Joseph Krummenacher (2006), "Cross-Trial Priming in Visual Search for Singleton

Conjunction Targets: Role of Repeated Target and Distractor Features," *Perception & Psychophysics*, 68 (5), 736–49.

Geyer, Thomas, Michael Zehetleitner, and Herman J. Müller (2010), "Contextual Cueing of Pop-out Visual Search: When Context Guides Deployment of Attention," *Journal of Vision*, 10 (5), 20–11.

Godwin, Hayward J., Michael C. Hout, and Tamaryn Menneer (2014), "Visual Similarity Is Stronger than Semantic Similarity in Guiding Visual Search for Numbers," *Psychonomic Bulletin & Review*, 21 (3), 689–95.

Godwin, Hayward J., Stephen C. Walenchok, Joseph W. Houpt, Michael C. Hout, and Stephen D. Goldinger (2015), "Faster than the Speed of Rejection: Object Identification Processes during Visual Search for Multiple Targets," *Journal of Experimental Psychology: Human Perception and Performance*, 41 (4), 1007–20.

Goldstein, Daniel G., Siddharth Suri, R. Preston McAfee, Matthew Ekstrand-Abueg, and Fernando Diaz (2014), "The Economic and Cognitive Costs of Annoying Display Advertisements," *Journal of Marketing Research*, 51 (6), 742–52.

Gollwitzer, Peter M., and Paschal Sheeran (2006), "Implementation Intentions and Goal Achievement: A Meta-Analysis of Effects and Processes," *Advances in Experimental Social Psychology*, 38, 69–119.

Gottlieb, Jacqueline P., Makoto Kusunoki, and Michael E. Goldberg (1998), "The Representation of Visual Salience in Monkey Parietal Cortex," *Nature*, 391 (6666), 481–4.

Hoban, Paul R., and Randolph E. Bucklin (2015), "Effects of Internet Display Advertising in the Purchase Funnel: Model-Based Insights from a Randomized Field Experiment," *Journal of Marketing Research*, 52 (3), 375–93.

Huang, Yanliu, and J. Wesley Hutchinson (2013), "The Roles of Planning, Learning, and Mental Models in Repeated Dynamic Decision Making," *Organizational Behavior and Human Decision Processes*, 122 (2), 163–76.

IAB (2020), "Internet Advertising Revenue Report: Full Year 2019 Results & Q1 2020 Revenues," https://www.iab.com/wp-content/uploads/2020/05/FY19-IAB-Internet-Ad-Revenue-Report_Final.pdf. Accessed April 9, 2021.

Inman, J. Jeffrey, Russell S. Winer, and Rosellina Ferraro (2009), "The Interplay among Category Characteristics, Customer Characteristics, and Customer Activities on in-Store Decision Making," *Journal of Marketing*, 73 (5), 19–29.

Ipata, Anna E., Angela L. Gee, Jacqueline Gottlieb, James W. Bisley, and Michael E. Goldberg (2006), "LIP Responses to a Popout Stimulus Are Reduced If It Is Overtly Ignored," *Nature Neuroscience*, 9 (8), 1071–6.

Itti, Laurent, and Christof Koch (2001), "Computational Modelling of Visual Attention," *Nature Reviews. Neuroscience*, 2 (3), 194–203.

Kireyev, Pavel, Koen Pauwels, and Sunil Gupta (2016), "Do Display Ads Influence Search? Attribution and Dynamics in Online Advertising," *International Journal of Research in Marketing*, 33 (3), 475–90.

Lambrecht, Anja, and Catherine Tucker (2013), "When Does Retargeting Work? Information Specificity in Online Advertising," *Journal of Marketing Research*, 50 (5), 561–76.

Lamy, Dominique, Charlie Antebi, Neta Aviani, and Tomer Carmel (2008), "Priming of Pop-Out Provides Reliable Measures of Target Activation and Distractor Inhibition in Selective Attention," *Vision Research*, 48 (1), 30–41.

Lewis, Randall A., and David H. Reiley (2014), "Online Ads and Offline Sales: Measuring the Effect of Retail Advertising via a Controlled Experiment on Yahoo!," *Quantitative Marketing and Economics*, 12 (3), 235–66.

Li, Hongshuang (Alice), and P. K. Kannan (2014), "Attributing Conversions in a Multichannel Online Marketing Environment: An Empirical Model and a Field Experiment," *Journal of Marketing Research*, 51 (1), 40–56.

Lien, Mei-Ching, Eric Ruthruff, Zachary Goodin, and Roger W. Remington (2008), "Contingent Attentional Capture by Top-Down Control Settings: Converging Evidence from Event-Related Potentials," *Journal of Experimental Psychology. Human Perception and Performance*, 34 (3), 509–30.

Luria, Saul M., and Mark S. Strauss (1975), "Eye Movements during Search for Coded and Uncoded Targets," *Perception & Psychophysics*, 17 (3), 303–8.

Maljkovic, Vera, and Ken Nakayama (1994), "Priming of Pop-Out: I. Role of Features," *Memory & Cognition*, 22 (6), 657–72.

Manchanda, Puneet, Jean-Pierre Dubé, Khim Yong Goh, and Pradeep K. Chintagunta (2006), "The Effect of Banner Advertising on Internet Purchasing," *Journal of Marketing Research*, 43 (1), 98–108.

McPeek, Robert M., and Edward L. Keller (2002), "Saccade Target Selection in the Superior Colliculus during a Visual Search Task," *Journal of Neurophysiology*, 88 (4), 2019–34.

McPeek, Robert M., Vera Maljkovic, and Ken Nakayama (1999), "Saccades Require Focal Attention and Are Facilitated by a Short-Term Memory System," *Vision Research*, 39 (8), 1555–66.

Milosavljevic, Milica, Vidhya Navalpakkam, Christof Koch, and Antonio Rangel (2012), "Relative Visual Saliency Differences Induce Sizable Bias in Consumer Choice," *Journal of Consumer Psychology*, 22 (1), 67–74.

Park, Sang Kyu, and Aner Sela (2020), "Product Lineups: The More You Search, the Less You Find," *Journal of Consumer Research*, 47 (1), 40–55.

Pashler, Harold, James C. Johnston, and Eric Ruthruff (2001), "Attention and Performance," *Annual Review of Psychology*, 52, 629–51.

Rossiter, John R., and Percy Larry (1997), *Advertising Communications and Promotion Management*, 2nd edition. New York: McGraw-Hill.

Rutz, Oliver J., and Randolph E. Bucklin (2012), "Does Banner Advertising Affect Browsing for Brands? Clickstream Choice Model Says Yes, for Some," *Quantitative Marketing and Economics*, 10 (2), 231–57.

Sahni, Navdeep S., Sridhar Narayanan, and Kirthi Kalyanam (2019), "An Experimental Investigation of the Effects of Retargeted Advertising: The Role of Frequency and Timing," *Journal of Marketing Research*, 56 (3), 401–18.

Saint Clair, Julian K., and Mark R. Forehand (2020), "The Many-Faced Consumer: Consumption Consequences of Balancing Multiple Identities," *Journal of Consumer Research*, 46 (6), 1011–30.

Sawaki, Risa, and Steven J. Luck (2010), "Capture versus Suppression of Attention by Salient Singletons: Electrophysiological Evidence for an Automatic Attend-to-Me Signal," *Attention, Perception, & Psychophysics*, 72 (6), 1455–70.

Schwarz, Wolf, and Anne-Kathrin Eiselt (2012), "Numerical Distance Effects in Visual Search," *Attention, Perception, & Psychophysics*, 74 (6), 1098–103.

Shen, Jianshong (2003), "On the Foundations of Vision Modeling I. Weber's Law and Weberized TV Restoration," *Physica D: Nonlinear Phenomena*, 175 (3-4), 241–51.

Shi, Savannah Wei, Michel Wedel, and Rik Pieters (2013), "Information Acquisition during Online Decision Making: A Model-Based Exploration using Eye-Tracking Data," *Management Science*, 59 (5), 1009–26.

Smith, Philip L., and Roger Ratcliff (2004), "Psychology and Neurobiology of Simple Decisions," *Trends in Neurosciences*, 27 (3), 161–8.

Stilley, Karen M., J. Jeffrey Inman, and Kirk L. Wakefield (2010), "Planning to Make Unplanned Purchases? The Role of in-Store Slack in Budget Deviation," *Journal of Consumer Research*, 37 (2), 264–78.

Stroud, Michael J, Tamaryn Menneer, Elina Kaplan, Kyle R. Cave, and Nick Donnelly (2019), "We Can Guide Search by a Set of Colors, But Are Reluctant to Do It," *Attention, Perception, & Psychophysics*, 81 (2), 377–406.

Thompson, Kirk G., and Narcisse P. Bichot (2005), "A Visual Salience Map in the Primate Frontal Eye Field," *Progress in Brain Research*, 147, 249–62.

Thota, Sweta Chaturvedi, Ji Hee Song, and Abhijit Biswas (2012), "Is a Website Known by the Banner Ads It Hosts?," *International Journal of Advertising*, 31 (4), 877–905.

Towal, R. Blythe, Milica Mormann, and Christof Koch (2013), "Simultaneous Modeling of Visual Saliency and Value Computation Improves Predictions of Economic Choice," *Proceedings of the National Academy of Sciences of the United States of America*, 110 (40), E3858–E3867.

Treisman, Anne, and Gordon Gelade (1980), "A Feature-Integration Theory of Attention," *Cognitive Psychology*, 12 (1), 97–136.

van der Lans, Ralf, Rik Pieters, and Michel Wedel (2008a), "Competitive Brand Salience," *Marketing Science*, 27 (5), 922–461.

—— (2008b), "Eye-Movement Analysis of Search Effectiveness," *Journal of the American Statistical Association*, 103 (482), 452–61.

van der Lans, Ralf, and Michel Wedel (2017), "Eye Movements during Search and Choice," in *Handbook of Marketing Decision Models*, 2nd edition, ed. Berend Wierenga and Ralf van der Lans, New York: Springer, 331–59.

van der Lans, Ralf, Michel Wedel, and Rik Pieters (2011), "Defining Eye-Fixation Sequences across Individuals and Tasks: The Binocular-Individual Threshold (BIT) Algorithm," *Behavior Research Methods*, 43 (1), 239–57.

Wagemans, Johan, James H. Elder, Michael Kubovy, Stephen E. Palmer, Mary A. Peterson, Manish Singh, and Rüdiger von der Heydt (2012), "A Century of Gestalt Psychology in Visual Perception: I. Perceptual Grouping and Figure-Ground Organization," *Psychological Bulletin*, 138 (6), 1172–217.

Wedel, Michel, and Chen Dong (2020), "BANOVA: Bayesian Analysis of Experiments in Consumer Psychology," *Journal of Consumer Psychology*, 30 (1), 3–23.

Wedel, Michel, and Rik Pieters (2015), "The Buffer Effect: The Role of Color When Advertising Exposures Are Brief and Blurred," *Marketing Science*, 34 (1), 134–43.

Wolfe, Jeremy M. (1994), "Guided Search 2.0: A Revised Model of Visual Search," *Psychonomic Bulletin & Review*, 1 (2), 202–38.

Wolfe, Jeremy M., and Todd S. Horowitz (2004), "What Attributes Guide the Deployment of Visual Attention and How Do They Do It?," *Nature Reviews Neuroscience*, 5 (6), 495–7.

Xu, Lizhen, Jason A. Duan, and Andrew Whinston (2014), "Path to Purchase: A Mutually Exciting Point Process Model for Online Advertising and Conversion," *Management Science*, 60 (6), 1392–412.

Zanto, Theodore P., and Jesse Rissman (2015), "Top-down Suppression," in *Brain Mapping: An Encyclopedic Reference*, Vol. 3, ed. Arthur W. Toga. Academic Press/Elsevier, 261–7.

Zehetleitner, Michael, Anja Isabel Koch, Harriet Goschy, and Hermann Joseph Müller (2013), "Salience-Based Selection: Attentional Capture by Distractors Less Salient than the Target," *PLoS One*, 8 (1), e52595.

Zhang, Jie, Michel Wedel, and Rik Pieters (2009), "Sales Effects of Attention to Feature Advertisements: A Bayesian Mediation Analysis," *Journal of Marketing Research*, 46 (5), 669–81.