Ad Click Prediction: Learning from Cognitive Style

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Abstract. In the past two decades, online advertising increased rapidly. It is now an integral part of the web experience. In this study, we divide webpages into two types: image-based and text-based webpages. We also differentiate user cognitive style as verbalizers and visualizers. Then we investigate how user's visual preference and the webpage type jointly influence the click-through rates of online flash ads. Our empirical results indicate that visual preference can significantly increase the click probability of flash ads. In addition, flash ads on text-based webpages are more likely to draw the attention of those users who prefer visual materials than on image-based webpages. Our findings contribute to the literature of online advertising by explaining how cognitive style and page context jointed affect ad click probability and providing guidelines for advertisers to target users more precisely.

Keywords: Cognitive style · Webpage type · Exposure frequency · Online flash ad

1 Introduction

In recent years, even though online advertising revenues have grown dramatically, click-through rates (CTR) for online advertising continue to decrease, raising hard questions regarding its effectiveness of targeting users [1]. Online users tend to pay more attention to the payload of the page and it is difficult for an ad to draw users' attention [2]. Improving advertising effectiveness is imperative for both advertising practitioners and academics [3].

Advertisers need to match online ads to relevant consumers. For example, advertisers try to match ad contents to user characteristics or webpage contents. Regarding the webpage content, it could include plain text, hyperlinks, graphics, audio, and video. In this study, if the main content of a webpage is images, e.g., pictures of a car on a dealer's website, it is an image-based page. If the main content is text, as typical in news portals, it is a text-based page.

Cognitive style theory suggests that users with different cognitive style have significant differences in inspecting learning materials [4]. Some people tend to spend more time inspecting visual materials such as picture or video. They are known as visualizers. Others tend to spend more time inspecting texts, known as verbalizers. This study uses visual (verbal) preference to refer to an individual's preference for processing visual (verbal) information. Nevertheless, cognitive style may affect users'

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allocation of cognitive resource when browsing an image-based or text-based page. It could also affect their responses to online ads which could be displayed in a visual or verbal webpage.

In this study, we use clickstream data provided by a China's digital advertising agency to explore how ad exposure frequency, cognitive style, and webpage type jointly affect the click-through rates of image-based online flash ads. The key research question is whether visualizers and verbalizers differ in their ad click behaviors in different webpage contexts.

Our results show that ad exposure frequency has a positive effect on the ad click probability in both image-based and text-based pages. Visual preference has a positive effect on the click-through rate of online flash ads. For interaction effect, flash ads on text-based webpages are more likely to draw visualizers' attention than those on image-based webpages.

The remainder of this paper is organized as follows: Sect. 2 reviews the literature related to online advertising and cognitive style theory. Rooted in previous literature, we propose our hypotheses in Sect. 3. Section 4 reports data collection and variable measurement. Section 5 reports model development and estimation results. Finally, in Sect. 6, we provide a discussion, managerial implication, limitations, and directions for future research.

2 Theoretical Background

2.1 Online Advertising System

An instance of online advertising comprises of three dimensions: the ad, the user, and the medium context. In this system, advertisers place their ads on a webpage to attract the attention of online users. Online users tend to regard the ad as an integral component of the page [2]. Therefore, the effectiveness of online advertising depends on not only the ad itself but also user characteristics and medium context.

The first dimension of advertising effectiveness is the properties of an ad, such as ad content, display format, and exposure frequency [3]. Numerous research and practice have examined the effects of different ad properties on its effectiveness. For example, Lee et al. [5] analyzed the effects of display format and ad repetition on user attention. They found that static banner ads are better in attracting and holding users' attention in the very beginning. However, the gaze duration to static ads rapidly decreased with repetition, while the gaze duration to animated ads decreases relatively slowly.

The second dimension of ad effectiveness is user characteristics. User characteristics usually comprise of demographics and behavioral information, which has been demonstrated to affect click-through rates of online ads [6]. Through integrating ad properties and user characteristics, advertisers can deliver their ads to specific user groups based on demographic information or behavioral features. For example, if a user has filled in car-related online forms or browsed car-related webpages, car ads could be delivered to the user when she surfs online.

The third dimension of online advertising is to deliver an ad in the right page context. A user's browsing behavior always occurs in a medium context. Therefore, medium features play a significant role in advertising effectiveness. Some studies have analyzed the effects of medium properties on ad effectiveness. Hsieh and Chen [2] examined how the information types of webpages influence the viewer's attention on banner advertising. Their study found that viewer's attention is stronger for image-based and video-based webpage than for text-based or text–picture mixed webpage. Other studies have attempted to enhance ad effectiveness by matching ads to relevant websites [7]. The underlying assumption is that ads that match the content of the page are relevant to the need of the user.

2.2 Cognitive Style Theory

The term 'cognitive style', which was first used by Allport [8], has been defined as a person's typical or habitual mode of problem-solving, thinking, perceiving, and remembering. Cognitive styles are often defined with bipolar dimensions, among which the verbalizer-visualizer style is one of the most fundamental dimensions [4]. The rationale of the verbalizer-visualizer cognitive style stems from the Dual Coding Theory (DCT), which states that verbal and nonverbal mental systems are specialized for processing linguistic and imagery information, respectively [9]. According to DCT, the verbalizer-visualizer style indicates whether an individual is inclined to mentally represent information in a verbal or visual form.

A wide range of studies on learning behavior has suggested that the verbalizer-visualizer cognitive style and the presentation of information interact to affect learning performance [10, 11]. A basic tenet is that individuals can achieve a better performance when they have the opportunity to receive their preferred presentation of information [12]. That is, verbalizers learn best from the text, while visualizers are better off with visual presentations. Although the DCT indicates that most individuals are capable of switching between verbal and nonverbal mental systems, they seem to find a particular mode easier to comprehend and to heavily rely on that information processing mode [13].

In recent years, eye-tracking technology has been increasingly used as a method to identify users' preference for verbal or visual presentation instead of traditional questionnaires [14]. Tsianos et al. [15] have used eye-tracking to identify users' actual behavior in adaptive e-learning systems. Their findings reveal that visualizers concentrate on visual content, verbalizers on text, while intermediates are placed in-between. Koć-Januchta et al. [16] have investigated the gaze behavior of college students and found that visualizers spend significantly more time inspecting pictures than verbalizers, while verbalizers spend more time inspecting texts. These results further verify that there are significant differences in the cognitive preference of different types of users.

3 Hypothesis Development

Most previous research on online advertising has focused on one or two advertising dimensions to improve ad effectiveness. In this paper, we integrate ad properties, user, and media into a unified framework and investigate how ad exposure frequency, user cognitive style, and webpage content type jointly and interactively influence the click-through rates of online flash ads.

3.1 Ad Exposure Frequency

For any online ad, exposure frequency is the fundamental factor that influences the persuasiveness of communications [17]. Previous studies examining the effects of repetition on message recall (the memory of the stimulus, i.e., brand name, advertising content) have found a positive effect of advertising repetition on consumers' recall [18, 19]. Repeating advertising to consumers boosts content learning and eventually results in action, such as a click or a sale [20]. Some studies have found that increased exposures to advertising are positively related to repeat purchase probabilities [21]. Thus, we expect that repeated ad exposures will generally increase the click-through rates of online ads.

In this study, we define two types of webpage: image-based webpage and text-based webpage. The former refers to webpages that dominantly contain pictures, and the latter refers to webpages that dominantly contain text. For each user, we count the ad exposure frequency on the two types of webpages separately. Without considering the impact of other factors, exposure frequency should have a positive effect on the click-through rates of online advertising, regardless of the page type. Thus, we hypothesize:

H1: The ad exposure frequency on image-based webpages has a positive effect on the click-through rate of an online flash ad.
H2: The ad exposure frequency on text-based webpages has a positive effect on the click-through rate of an online flash ad.

3.2 The Match Between Cognitive Style and Ad Format

The cognitive style theory indicates that the cognitive style could be a critical factor affecting users' attention to stimuli in different formats. However, until recently, cognitive style is rarely utilized by advertisers. Although advertisers have developed various methods to optimize an ad for users, they have not found a way to personalize their ad based on users' cognitive style [1].

Chiou et al. [22] compared the effectiveness of traditional textual brochures with image-based virtual advertising which provides panoramic views, animation, and interactive photos for both visualizers and verbalizers. They found that traditional brochures are more effective for verbalizers, whereas virtual advertising is more effective for visualizers. Urban et al. [23] have dynamically changed banner ads based on the inferred cognitive style of users, including impulsive-analytic, impulsive-holistic, deliberative-analytic, and deliberative-holistic dimensions. Their experimental results show that ads matched to cognitive styles increase click-through rates, brand consideration, and purchase likelihood.

We believe visualizers and verbalizers can be inferred based users' browsing history, and matching online ads to inferred cognitive style would boost click-through rate. All online ads in our dataset are flash images. We use the percentage of image-based webpages a user has browsed in comparison to the total number of pages he has browsed to gauge her visual preference. Based on the literature, because image ad matches the cognitive style of visualizers, visualizers are more likely to click online flash ads. Thus, we hypothesize:

H3: A user's visual preference is positively associated with the click-through rate of an online flash ad.

3.3 The Match Among Ad, User, and Media

A webpage, either image-based or text-based, demands user attention cognition. Online ads, as a component of webpages, compete with other webpage elements for users' attention. When clicking an online ad, a user's attention shifts from the webpage content to the ad. Previous research has found that a user shifts her attention to an information object which is more efficient to process, and shifts away her attention from an unwanted or irrelevant object [24].

For visualizers, when they are browsing image-based webpages, we expect that a flash ad is less likely to distract their attention away from the webpage content. This is because an image-based webpage already has more relevant and easy-to-process images for visualizers. An ad is neither a more relevant object nor an easier-to-process object to process. Consequently, visualizers are unwilling to shift their attention to ads.

In contrast, when visualizers are browsing text-based webpages, an image-based flash ad is more likely to distract their attention away from the webpage text. This is because the text in such webpages is cognitively more costly for visualizers. A flash ad, even if it is less relevant to the user, is more likely to attract users' attention.

Based on the above reasoning, flash ads on text-based webpages are more likely to draw visualizers' attention than those on image-based webpages. Consequently, the effect of the exposure frequency on the click-through rate will be attenuated by visual preference on image-based webpages but be strengthened on text-based webpages.

H4: The effect of ad exposure frequency on the click-through rates of online flash ads on image-based webpages will be negatively moderated by visual preference.
H5: The effect of ad exposure frequency on the click-through rates of online flash ads on text-based webpages will be positively moderated by visual preference.

4 Research Methodology

4.1 Data Collection

We use secondary data provided by a China's digital advertising agency to test our hypotheses. From August 18, 2014 to December 31, 2014, the agency launched 42 online advertising campaigns that involved 11 car brands and five media websites. Each campaign displayed ads of a specific car brand on a specific media website. We randomly selected one advertising campaign, which was conducted from October 1, 2014 to October 31, 2014. The selected campaign delivered the ads of a Japanese car on Bitauto.com. We obtained users' browsing history on all five websites covered by the agency from August 18, 2014 to October 31, 2014. Eventually, we had 215,477 users.

4.2 Variable Measurement

Dependent Variables. In our dataset, each ad exposure was tagged to indicate whether the ad was clicked. We use *Click* to represent the status of ad click. If a user has clicked ads at least once, we set *Click* to one. Meanwhile, we used browsing history before the user's first ad click to calculate independent and control variables. Otherwise, we set *Click* to zero and used the full browsing history of the user to calculate independent variables.

Independent Variables. First, we created two variables to represent the ad exposure frequency to each user for the selected campaign. *ExpVisual* represents the ad exposure frequency in image-based webpages before user's first click, and *ExpVerbal* represents the ad exposure frequency in text-based webpages before user's first click. The classification of image-based and text-based pages in the automobile portal websites is straightforward. While most pages are text-based, each model of car has a few image-based pages which display various pictures of the model. These image pages have a clear URL pattern. Since there was a large number of zero values for the two variables (i.e., some users had ad exposure only on text-based pages or image-based pages), we created two dummy variables *DumVisual* and *DumVerbal* to indicate whether a user has browsed ads in image-based webpages or text-based webpages respectively. Second, we defined a variable *RatioVisual* to denote a user's ratio of browsing image-based webpages over all pages the user browsed. It gauges users' visual preference or their degree of being a visualizer. After removing duplicate URLs, we used browsing history of all campaigns in our dataset to calculate *RatioVisual*.

Control variables. To control user heterogeneity, we also coded additional variables according to users' browsing history. First, we included ad-related control variables. *ExpDay* represents the number of days when users have been exposed to the ad of the selected campaign. *AdAccept* represents a user's ratio of clicking ads across all ad exposures of all campaigns. This variable gauges users' propensity to click online ads. Second, we controlled the user preference for different cars. The advertised car in the selected campaign is a medium-sized and medium-priced car[1]. Thus, we used *RatioSize* to represent user's ratio of browsing medium-sized cars across all websites. We used *RatioPrice* to represent user's ratio of browsing medium-priced car models. Third, we also controlled user's preference to auto-related websites. *NumSite* represents the

[1] Bitauto.com tags the cars with prices between 180,000 RMB and 250,000 RMB as medium-priced ones.

Table 1. Definitions and basic descriptive statistics of variables

Variable	Definition	Mean	S.D.	Min	Max
Click	A binary variable indicating whether a user clicked on an ad in the selected campaign	0.005	–	0	1
ExpVisual	Ad exposure frequency in image-based webpages in the selected campaign	3.877	10.368	0	595
ExpVerbal	Ad exposure frequency in text-based webpages in the selected campaign	1.238	2.323	0	129
DumVisual	A dummy variable indicating whether a user browsed ads in image-based webpages in the selected campaign	0.615	–	0	1
DumVerbal	A dummy variable indicating whether a user browsed ads in text-based webpages in the selected campaign	0.536	–	0	1
RatioVisual	The ratio of browsing image-based webpages in all campaigns of our dataset	0.424	0.365	0	1
ExpDay	The number of days when users have been exposed to the ad in the selected campaign	1.645	1.423	1	29
AdAccept	The ratio of clicking ads in all campaigns	0.002	0.018	0	1
RatioSize	The ratio of browsing medium-size car webpages in all campaigns	0.265	0.197	0.001	1
RatioPrice	The ratio of browsing medium-priced car webpages in all campaigns	0.034	0.101	0	0.952
NumSite	The number of auto websites that a user has visited in all campaigns	1.653	0.809	1	5
RatioBitauto	The ratio of browsing Bitauto.com webpages in all campaigns	0.801	0.289	0.002	1
UrlAll	The number of unique webpages that a user has visited in all campaigns	19.252	24.740	1	896
UrlDaily	The daily average number of webpages that a user has visited in all campaigns	1.845	1.018	0.500	228.667
NumCity	The number of cities where a user's IP address has ever appeared in all campaigns	1.360	0.879	1	74

number of websites that a user has visited in all campaigns. *RatioBitauto* represents the ratio of browsing Bitauto.com in all campaigns. Next, we defined two variables to measure user activeness. *UrlAll* represents the number of unique webpages that a user has visited. *UrlDaily* represents the daily average number of unique webpages that a user has visited, which equals *UrlAll* divided by *ExpDay*. Finally, considering that users' geographic mobility may also affect automobile ad clicks, we create a variable *NumCity* to represent the number of cities where a user's IP address has ever appeared. Table 1 illustrates the definition and the basic descriptive statistics of all variables.

5 Empirical Analysis

5.1 Model Development

We used a logit model to analyze users' ad click behavior. We model users' ad click probability as a function of exposure frequency, cognitive style, page type, and other control variables. We assume that users' latent utility determines their ad click behaviors. For a user *i,* we use $Click_i$ to denote the user's binary response and U_i to denote the user's latent utility.

$$Click_i = \begin{cases} 1, \ if \ U_i > 0 \\ 0, \ if \ U_i \leq 0 \end{cases} \quad where \ U_i = v_i + \varepsilon_i \tag{1}$$

The main part of U_i is represented by v_i, which is a linear function of the independent and control variables. The second part ε_i is the stochastic component, which contains non-systematic or random factors affecting U_i. When users are exposed to an ad on the webpage, they click on the ad only if their latent utility U_i is greater than zero.

By applying a logit model, we aim to measure the effects of cognitive style and ad exposures on click-through rates of online ads. We also aim to examine the interactions between cognitive style and exposure frequency on different types of webpage. The utility function of our model is as follows:

$$\begin{aligned} U_i = {} & \beta_0 + \beta_1 ExpVisual_i + \beta_2 DumVisual_i + \beta_3 ExpVerbal_i + \beta_4 DumVerbal_i \\ & + \beta_5 RatioVisual_i + \beta_6 ExpDay_i + \beta_7 AdAccept_i + \beta_8 RatioSize_i + \beta_9 Ratio\,\mathrm{Pr}\,ice_i \\ & + \beta_{10} NumSite_i + \beta_{11} RatioBitauto_i + \beta_{12} UrlAll_i + \beta_{13} UrlDaily_i + \beta_{14} NumCity_i \\ & + \beta_{15} RatioVisual_i * ExpVisual_i + \beta_{16} RatioVisual_i * ExpVerbal_i + \varepsilon_i \end{aligned} \tag{2}$$

5.2 Estimation Results

For comparison, we first converted *ExpVisual*, *ExpVerbal*, *UrlAll*, *UrlDaily*, and *NumCity* to its natural logarithm values. Then, we standardized all variables except for binary ones.

We present the estimation results in Table 2. Model 1 is the main effect model without consideration of the interaction between cognitive style and exposure frequency. In this model, the coefficient of *ExpVisual* is significantly positive. Thus, the exposure frequency on image-based webpages has a significantly positive effect on the ad click probability. This finding supports H1. Similarly, the result of Model 1 also

Table 2. Estimation results

	Model 1	Model 2	Model 3
ExpVisual	0.316*** (0.042)	0.429*** (0.045)	0.406*** (0.046)
DumVisual	1.093*** (0.155)	0.650*** (0.183)	0.480* (0.189)
ExpVerbal	0.420*** (0.104)	0.314*** (0.107)	0.466*** (0.117)
DumVerbal	−0.664*** (0.155)	−0.620*** (0.155)	−0.882*** (0.178)
RatioVisual	1.166*** (0.178)	1.498*** (0.191)	1.717*** (0.198)
ExpDay	−0.752*** (0.046)	−0.736*** (0.046)	−0.732*** (0.046)
AdAccept	3.579*** (0.602)	3.585*** (0.589)	3.523*** (0.605)
RatioSize	4.928*** (0.235)	5.125*** (0.243)	5.126*** (0.241)
RatioPrice	2.385*** (0.566)	2.489*** (0.567)	2.510*** (0.562)
NumSite	0.072 (0.056)	0.061 (0.056)	0.067 (0.056)
RatioBitauto	1.683*** (0.243)	1.685*** (0.243)	1.723*** (0.242)
UrlAll	1.747*** (0.082)	1.773*** (0.082)	1.767*** (0.081)
UrlDaily	−1.527*** (0.144)	−1.479*** (0.145)	−1.469*** (0.145)
NumCity	0.032 (0.070)	0.034 (0.070)	0.035 (0.070)
RatioVisual*ExpVisual		−0.495*** (0.194)	−0.464*** (0.108)
RatioVisual*ExpVerbal			0.822*** (0.218)
Constant	−6.631*** (0.181)	−6.305*** (0.194)	−5.967*** (0.222)
N	215,477	215,477	215,477
Log Likelihood	−5607.89	−5598.77	−5591.36
Pseudo R2	0.1364	0.1378	0.1390

Standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

shows that the exposure frequency on text-based webpages has a significantly positive effect on the ad click probability, which supports H2. Besides, the coefficient of *DumVisual* is significantly positive while *DumVerbal* is significantly negative, which indicates that users are more likely to click online flash ads on image-based webpages. This is because processing image-based webpage requires less mental resource so that more attention is available for ads on the webpage. As for cognitive style, the coefficient of *RatioVisual* is significantly positive. That is, a visualizer has a higher probability of clicking online flash ads. This finding supports H3.

Next, we included the interaction of cognitive style and ad exposure frequency on image-based webpages in Model 2. The model shows that the coefficient of the interaction between *RatioVisual* and *ExpVisual* is significantly negative. Then, we continued to include the interaction of cognitive style and ad exposure frequency on text-based webpages in Model 3. The coefficient of the interaction between *RationVisual* and *ExpVerbal* is significantly positive. The two findings indicate that those users who prefer visual materials are more inclined to click flash ads on text-based webpages than on image-based webpages. More specifically, the effect of ad exposure frequency on image-based webpages on the click-through rates of online flash ads is attenuated by visual preference. However, the effect is strengthened visual preference on text-based webpages. The results support H4 and H5.

6 Discussion and Conclusions

This paper empirically investigates how cognitive style affects users' response to flash ads displayed in different webpage types. We divide webpages into two types: image-based webpages and text-based webpages. Then, we examine the effects of exposure frequency on these two types of webpages and cognitive style on users' ad click behavior. Besides, we also explore whether and how cognitive style moderates exposure frequency on ad click behavior. Our results indicate that exposure frequency has a positive main effect on ad click behavior. Cognitive style also has a significant impact on users' response to flash ads. Users with a higher visual preference are more likely to click flash ads. For the interaction effect between exposure frequency and cognitive style, we find that the effect of exposure frequency on flash ad click in image-based webpages is attenuated by visual preference. Conversely, the effect of exposure frequency on ad click in text-based webpages is strengthened by visual preference. The findings of our study offer several implications for research and practice, which are discussed as follows.

6.1 Theoretical Implications

First, this study contributes to the literature of online advertising by utilizing cognitive style theory to predict ad click probability, which has not been investigated before. Cognitive style theory has been widely applied to learning behaviors. Our findings suggest that cognitive style plays a significant role in affecting users' response to online ads. This perspective provides a valuable complement for existing target methods such as context matching, demographic matching, and behavioral matching.

Second, this study integrates advertising characteristics, user characteristics, and media context into a unified framework from the cognitive style perspective. We investigate the interaction effects between cognitive style and exposure frequency on different types of webpage. Our findings provide new insights regarding the interplay among various components in online advertising system. This may provide incremental lift beyond previous target patterns that only consider the match between any two parts.

6.2 Managerial Implications

The findings in our study also provide valuable guidelines for advertisers to target users more precisely. First, since cognitive style has a significant impact on ad click behavior, advertisers can reach customers based on their cognitive style in addition to their interest profile. Advertisers can infer cognitive style of online users by their browsing history and then selectively expose ads to users with corresponding cognitive style. For example, picture or video ads should be delivered to users who prefer browsing image-based webpages while text ads should be delivered to users who prefer browsing text-based webpages.

Second, besides the match between ad format and cognitive style, advertisers should also consider the impact of media context. For example, in terms of delivering flash ads to users with visual preference, exposures on text-based webpages may result in higher click-through rates than on image-based webpages.

6.3 Limitation and Future Directions

There are some limitations to this study. First, because of the limitation of secondary data, we can only approximately measure users' cognitive style by the ratio of browsing image-based webpages. Future study should verify our results by more accurate measurement of cognitive style, such as survey or eye-tracking technology. Second, we only consider the effects of exposure frequency and two types of webpage structures on ad click. Future study could extend our results by including more ad-related factors and media context. Finally, there is still some confusion about how cognitive style interacts with media context. Figuring out the mechanism with a more informative dataset could further elucidate the pivotal effect of cognitive style in online advertising system and enhance the understanding of this field.

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