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Abstract: With the development of multimedia, the form of online advertising has become more diversified. In the increasingly competitive environment between e-commerce enterprises, the proportion of online advertising investment in total advertising investment continues to grow. However, the operating costs of enterprises are limited, in order to maximize the effectiveness of operating costs, evaluating the effect of various forms of online advertising effectively to determine the scientific online advertising budget allocation is crucial. Based on the enterprise's Web log data, we extract the characteristic variables that represent consumer's behavior including click behavior, visit behavior and purchase behavior. On the one hand, using multivariate linear regression method to assess the short-term effect of three forms of online advertising in an overall level. On the other hand, we use logistic regression models to investigate the impact of various consumer behaviors on the purchase conversion of consumers who enter the website from different advertising channels.

Keywords: Online advertising, Short-term effects, Purchase conversion

1. INTRODUCTION

The rapid development of Internet technology and the improvement of social informatization level provide a favorable environment for the development of enterprises. Under the trend of accelerating the integration of traditional media and new media, enterprises have realized the significance of Internet in the marketing system, and gradually shift the focus of marketing to the Internet. "2017 Annual Report on Online Advertising Market of China" released by IResearch indicates that revenue scale of online advertising increased from 33.71 billion RMB in 2010 to 290.27 billion RMB in 2016 with an annual growth rate of 43.1% [1]. It can be seen from the report that the revenue of online advertising is far higher than that of traditional advertising, consequently, it is more likely for enterprises to invest online advertising and expand input scale in the future.

However, the cost of online advertising keeps continuous rising, which has become the largest expenditure of enterprises' operating expenses. Furthermore, diversification of forms of online advertising has exacerbated the rise of advertising costs. Therefore, it is crucial for enterprises to figure out the effectiveness of different forms of online advertising so that they can determine scientific budget allocation to get the maximum profits. Besides, based on online environment, enterprises are capable to collect various user behaviors. For consumers who enter the website from different advertising sources, the impact of their behavior on purchase are different. The enlightenment gained from the analysis of consumer behavior is more valuable to marketing management.

2. LITERATURE REVIEW

2.1 Online advertising

In recent years, a large amount of the existing research focus on influential factors of specific advertising form's effectiveness. For example, Rutz and Trusov explained how position and content of paid search

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advertising influence its effectiveness [2]. Lambrecht and Tucker found that the effectiveness of retargeting depends on consumers' product preference [3]. These studies neglect to evaluate the effects of various forms of online advertising in an overall level and thus, are of limited value in enterprises' budget allocation decisions. Nottorf indicated that consumers are often influenced by more than one specific type of online advertising when they click advertising links to enter the website [4]. Consumers are usually exposed to several online advertisements before purchase. Then, what contribution will consumers' click behavior of various online advertisements have on following purchase? An overall assessment about the effects of various online advertising is needed.

Previous studies have shown that advertising has immediate and carryover effects on sales. The short-term effects of online advertising refer to a consumer's reaction to advertising exposure within a short period of time, such as clicks, purchases [5]. Bass and Clarke said that the largest impact of advertising may not necessarily be in the initial moment but work after a certain time [6], which emphasized the significance of carryover effects. Many studies worked on how to treat time lag, which only partially reflected short-term effects of advertising. Breuer and Brettel evaluated short- and long-term effects of display, e-mail, price comparison advertising using multiple linear regression models combined with time lag [5]. Haan *et al.* compared the long-term effectiveness of nine forms of online advertising by establishing a structure-vector autoregressive model and a restrictive impulse response, but their results did not indicate the evidence of time-varying parameters [7]. However, for enterprises, the short-term effects of online advertising can stimulate consumer purchases in a short period of time and bring sales revenue to enterprises more directly. This is undoubtedly a more attractive research topic for enterprises.

2.2 Short-term effects of online advertising

In recent years, researchers have noticed to evaluate effects of online advertising based on clickstream data. Yet, for commercial websites, clickstream data usually involves commercial secrets, thence studies may be limited by data availability and the findings in this area are still rare. Concluding from the existing research results, the evaluation of short-term effect mainly starts from click-through rate and conversion rate.

Click-through rate is the percentage of advertising clicks to total impressions. Among them, last-click model has been widely used in actual business management. However, it does not consider consumer's behavior and neglect other information before consumer's last click on online advertising. Although click-through rate shows an insufficient description, it still reflects the effectiveness of advertising to some extent. Some scholars also point out that click-through rate can be used as an intermediary variable to reflect other influential factors. Some studies explored impact of consumer's behavior on click possibility under different online advertising exposures. Chatterjee *et al.* built a measurement model of click probability by means of logistic regression to discuss the impact of advertising exposure period and impressions on click probability [8]. Nottorf investigated consumer click possibilities for display, redirect, paid search and video advertising using a binary logit with Bayesian mixture of normal based on similar consumer advertising browsing and clicking data [4].

Further than click-through rate, some scholars start to consider online advertising effects from the perspective of purchase intention [7]. Manchanda *et al.* measured impact of display advertising on purchase probability by establishing a survival model[9]. Summers *et al.* compared differences between effectiveness of targeted advertising based on online and offline environment by purchase intention. Compared with click-through rate, purchase intention as evaluation index of online advertising effect is closer to actual demand of enterprises [10].

Conversion rate represents the ratio of consumer conversion from potential customer to newers under the influence of online advertising. Rutz and Trusov designed a two-stage user transformation model to describe the process from click to purchase [2]. Similar to Rutz, Montgomery *et al.* used purchase conversion rate to further convert clicks into purchase possibilities and tried several models including multiple predictive model to fit consumer's browsing and clicking data [11]. Xu *et al.* studied dynamic interaction between online advertising clicks by using translation probability to discuss effects of online advertising [12]. Among these studies, the dataset they used are simple statistics of page browsing and advertising impressions before clicks. Few studies have examined short-term effects of online advertising from following visit behavior after consumers enter the website.

Considering that consumers' clicks on online advertising to enter the site is triggered by current advertising, thus subsequent behavior is what we believe to be affected by short-term effects of the advertising. And reviewing existing research, the question of connection between consumer behavior and purchase under the influence of different types of online advertising has not been discussed in depth. Therefore, based on data of a third-party insurance agent network platform, we chose to examine short-term effects of various types of online advertising and set up evaluation model based on purchase intention to construct the relationship of consumers' visit behavior and purchase behavior after they enter the site through online advertising. We concentrated on three types of online advertising—paid search, e-mail and short message service advertising, measured short-term effects of each adverting and figured out the specific contribution of various consumer behavior to purchase.

3. MODEL

The mainstream types of online advertising include display, paid search, e-mail and short message service advertising. As display advertising is increasingly perceived as disruptive to users, enterprises have curtailed their display advertising investment. Accordingly, our modeling work of short-term effects of online advertising and purchase conversion mechanisms is centered around paid search, e-mail and short message service advertising.

3.1 Short-term effects measurement

Based on previous studies, short-term effects of online advertising refer to behavior reaction of consumers in a short period of time after advertising exposures, which includes following click and purchase behavior. Considered actual demands of enterprises, direct response of advertising effects that enterprises can notice is the sales growth. In other words, the most intuitive reflection of short-term effects is on consumer purchase intention.

Earlier, Srinivasan and Weir proposed a direct aggregation approach that examines the advertising effect by establishing the relationship between advertising and sales [13], as follows:

$$S_t = a + bAdv_t^* + e_t \tag{1}$$

where S_t represents sales volume on day t, Adv_t^* represents advertising stock of each advertising on day t and the estimated parameter b indicates short-term effects of each advertising. The model takes advertising stock as an independent variable and considers the contributions of each advertising inputs to sales volume. The contributions are interpreted as short-term effects of each advertising. Since the model was proposed under offline environment, it was hard to track the profit that each consumer made under the impact of advertising. Therefore, it takes sales volume of the entire enterprise as dependent variable, which results that the sales income can't be differentiated from advertising and non-advertising caused. Currently, enterprises can track consumers' visit tours based on Web log so that effects of online advertising can be examined from consumer-level by modeling each consumer's behavior record. Studies have shown that user engagement, such as interaction with advertising, can lead to stronger predictive effects. Compared with advertising stock, consumers' clicks on advertising represent their willingness on advertising and predict possible purchase better, besides, it also confirms that subsequent purchase behavior is affected by advertising. Consequently, we try to establish connection between advertising clicks and purchase in short order. We consider consumer's clicks on each online advertising as independent variables and purchases volume as dependent variable to investigate short-term effects, where short-term effects are interpreted as impact of advertising click on purchase in short order. Proposed model is shown as equation (2):

$$S_{it} = a + \beta_1 SEA_{it} + \beta_2 SMS_{it} + \beta_3 EMA_{it} + e_{it} \tag{2}$$

where S_{it} means purchases volume of user i on day t; SEA_{it}, SMS_{it}, and EMA_{it} respectively represents clicks on paid search, short message service and e-mail advertising of user i on day t; β_1, β_2, β_3 are parameters to be estimated, which represents short-term effects of paid search, short message service and e-mail advertising.

3.2 Purchase conversion mechanism

In addition to an overall assessment of short-term effects of three types of online advertising, we attempt to construct purchase conversion mechanisms for various types of online advertising, which discusses the impact of subsequent visit behavior after consumers enter the website through online advertising on purchase. So, we consider a logistic regression model is suitable with whether consumer purchases or not as dependent variable, and a plurality of characteristic variables describing consumer's visit behavior as independent variables.

Reviewing previous studies, we extracted characteristic variables that describe customers' behavior from their visit tours. In marketing management, website purchase funnel is often used to describe a consumer's journey. Website purchase funnel mainly consists of four stages, first, a consumer usually lands on home page or product pages through advertising links. And then, he searches the website according to his need and views various product pages. In this process, he stores products that are possible to purchase in the shopping basket. After this, he would like to compare the products and finally make a purchase. By studying the literature describing this process systematically and combining actual experience, we summarize consumers' behavior that may influence purchase behavior during their stay on the site, including search, visit and interest behavior. Considering the functional design of the website and the actual data, eight characteristic variables of consumer behavior were extracted, including number of filtering, number of viewing pages, average time of viewing each page, number of viewing product pages, average time of viewing each product page, number of viewing "School" pages, number of viewing "Topic" pages, number of viewing "Toptag" pages. The specific model proposed is as equation (3):

$$h\left(Y^*\right) = p\left(purchase \middle| Y^*\right) = Logit\left(\beta Y^* + \varepsilon\right) = \left[1 + \exp\left(\alpha + \beta_1 y_1 + \beta_2 y_2 + \cdots + \beta_8 y_8\right)\right]^{-1} \tag{3}$$

where $h(Y^*)$ represents purchase flag; Y^* represents behavior characteristic variables of consumers from different advertising sources, y_i represents behavior characteristics; β_i is the parameter to be estimated, is also the influence coefficient, which is used to judge the impact of each user behavior on the final purchase behavior.

4. EMPIRICAL STUDY

4.1 Data pretreatment

The data we used is the Web log data of a third-party insurance agent network platform in Nanjing. The time period ranges from January 1st, 2017 to April 30th, 2017, and the total amount of original data exceeds 15 million user records. Web log data records consumer's click behavior, where each record represents a click behavior of the consumer. We aim to construct connection between consumer's visit behavior and purchase behavior. User identification is required to decide which records belong to the same person. After this, session segmentation helps us to figure out consumer’s behavioral sequence from entering the site to leaving. Finally, we extract characteristic variables that we proposed above from each session of each user. The data preparation process is as follows:

(1) Data acquisition: We obtain single-day PC terminal data from Web log and extract research related field information, such as IP, visit date, visit time, agent, cookie, etc.

(2) User identification: According to the extracted field information, we distinguish the users based on cookie, IP and agent field. There is a need to illustrate that cookie represents the web cache information generated by user visit behavior, while agent represents the user’s web browser.

(3) Session segmentation: We divide session by time threshold set between two adjacent access requests, and the threshold value is set to 1800 seconds. What needs to be explained here is that since the first model is an overall assessment, we believe that fetching variables on a daily basis is sufficient.

(4) Feature extraction: We extract users’ behavior characteristics of each session that is mentioned in the theoretical models. The specific variables are shown in table 1.

Table 1. Characteristic variables description

Variable	Name	Variable	Name
S_{it}	Purchases volume	y_4	Number of viewing product pages
SEA_{it}	Paid search advertising clicks	y_5	Average time of viewing each product page
SMS_{it}	Short message service advertising clicks	y_6	Number of viewing “Study” pages
EMA_{it}	E-mail advertising clicks	y_7	Number of viewing “Topic” pages
y_1	Number of filtering	y_8	Number of viewing “Toptag” pages
y_2	Number of viewing pages	$h(Y^*)$	Purchase flag
y_3	Average time of viewing each page		

4.2 RESULT

4.2.1 Short-term effects measurement

Based on the theoretical model (2), we extracted the clicks of paid search, short message service, e-mail advertising and purchases volume, and constructed the relationship between the clicks of each type of online advertising and purchases. The descriptive statistics and estimated parameters are respectively shown in table 2 and table 3.

Table 2. Descriptive statistics

	S_{it} (Purchases volum)	SEA_{it} (Paid search advertising clicks)	SMS_{it} (Short message service advertising clicks)	EMA_{it} (E-mail advertising clicks)
Sum	25404	610848	174	573

Table3. Parameter estimation of short-term effects

Parameter	Estimate	t value	Pr(>|t|)
α (Intercept)	-0.0063	-3.3790	0.0007
β_1 (Paid search advertising)	0.0463	38.1550	0.0000
β_2 (Short message service advertising)	0.0564	1.2840	0.1992
β_3 (E-mail advertising)	0.0811	3.5320	0.0004

From Table 3, we can see that P values of β_1 and β_3 are less than 0.05. It means clicks on paid search and e-mail advertising have a significant impact on purchase. Therefore, our resulting model is shown as equation (4).

$$S_{it} = -0.063 + 0.0463 \times SEA_{it} + 0.0811 \times EMA_{it} \tag{4}$$

Based on the estimation of β_1 and β_3 (0.0463: 0.0811), we find that impact of both paid search and email advertising on purchase are positive and the influence of email advertising is stronger than paid search advertising. We consider paid search advertising to be triggered by consumers' spontaneous searching behavior, which is driven by their interests, and therefore information provided by paid search advertising is related to consumers' preferences and current needs. E-mail advertising focuses on inferring consumers' preferences and distributing information to specific groups based on their visit or purchase history. In other words, paid search advertising is result of consumers' searching when they are aware of their own demands, thus its role is to stimulate consumers' willingness to make a purchase. While e-mail advertising can stimulate consumers to generate demand, and based on past visits and purchases, once existing consumers generate interests, they will be more prone to purchase. Therefore, we believe that e-mail advertising is more incentive to purchase than paid search advertising, and the result also indicates that the enterprise has done a good job of targeting e-mail advertising.

In term of short message service advertising, its impact of short message service advertising clicks on purchase is not significant. Combining Table 2, we can see that we have only got 174 total clicks of short message service advertising. This may be due to the limited investment of short message service advertising so that the clicks are few; otherwise, the distribution of the enterprise does not have a strong pertinence, that is, the content of short message service advertising does not match the preference of whom received the message. The enterprise spent advertising investment did not receive the expected effect, resulting in a waste of funds.

4.2.2 Purchase conversion mechanism

According to the theoretical model (3), we extract user behavior variables and try to respectively establish purchase conversion mechanism of paid search, email and short message service advertising. When we tried to construct purchase conversion mechanism of short message service advertising, all variables were insignificant, and considering its insignificant clicks on purchase, we will not discuss this purchase conversion mechanism.

1) Paid search advertising

We get dataset after data pretreatment and model records of consumers who enter by paid search advertising links to construct purchase conversion mechanism, the estimated parameters are shown in table 4.

Table 4. Parameter estimation of paid search advertising

Parameter	Estimate	t value	Pr(>|t|)
α (Intercept)	-4.9600	-208.760	0.0000
β_1 (Number of filtering)	-0.5185	-27.389	0.0000
β_2 (Number of viewing pages)	0.3943	143.241	0.0000
β_3 (Average time of viewing each page)	0.0004	5.018	0.0000
β_4 (Number of viewing product pages)	-0.3623	-59.622	0.0000
β_5 (Average time of viewing each product page)	-0.0004	2.050	0.0403
β_6 (Number of viewing "Study" pages)	-2.392	-26.257	0.0000
β_7 (Number of viewing "Topic" pages)	-0.6628	-2.911	0.0036
β_8 (Number of viewing "Toptag" pages)	-1.5740	-15.901	0.0000

As shown in Table 4, all parameters are significant, which means that all the behavioral characteristics have a significant impact on purchase conversion. Therefore, the resulting model is as equation (5):

$$h\left(Y^{SEA}\right)=\left[1+\exp\begin{pmatrix}-4.9600-0.5185y_1+0.3943y_2+0.0004y_3-0.3623y_4\\-0.0004y_5-2.3920y_6-0.6628y_7-1.5740y_8\end{pmatrix}\right]^{-1} \tag{5}$$

The parameters of number of viewing pages and average time of viewing each page (0.3943: 0.0004) are positive, which means that with more pages and longer stay that consumer viewing, purchase possibility will get higher, and the impact of former is much stronger than the later. Consumers who click on paid search advertising to enter a site may be unfamiliar with the site, they are in the process of exploring and searching for products, and therefore, the increase in the number of viewing pages and average time of viewing each page means that the functional design or product of the website causes consumer's interest, the purchase possibility will also rise.

In addition, all other variables have negative parameters, which means that all the other behaviors will have a negative impact on purchase intention.

The increase in the number of filtering means that the consumer constantly changes the filter conditions to search the product that meets their expectations, that is, most products may not satisfy the consumer, leading him to adjust priority of their demands to get a better choice. For example, a consumer needs to purchase travel insurance with a selected brand of China Ping An and the security coverage includes flight delays and money robberies. When he finds that there is no product that fits all the requirements, he has to re-determine filter conditions and may choose other brands to check the results. As a result, as the number of adjustments continues to increase, the consumer is less likely to find the desired product, and purchase probability falls.

As for number of viewing product pages and average time of viewing each product page on purchase, their impacts are just in contrast to number of viewing pages and average time of viewing each page, which we think is not contradictory. For consumers who land on the website by paid search advertising links, they are exploring, thus the increase in number of viewing pages is more likely caused by other functional pages rather than product pages, which represents a rise of consumers' interests to the website itself. It will promote purchase intention. While an increase in number of viewing product pages or average time of viewing each product page indicates that consumers are more hesitate to make a purchase. Therefore, it will lead to a decrease in purchase possibility.

Besides, the featured sections of the website are generally avenues for consumers seeking help when they doubt about some product or service, so the more pages viewed, the less likely a consumer's question will be resolved and the odds of a purchase occurring get lower.

2) E-mail advertising

We identify the records of consumers who enter the website through e-mail advertising links to establish the purchase conversion mechanism of e-mail advertising, where we find the number of viewing "Topic" pages among all records is null. Thus, we do not discuss this variable. The estimated parameters are shown in table 5.

Table 5. Parameter estimation of e-mail advertising

Parameter	Estimate	t value	Pr(>|t|)
α (Intercept)	-4.7250	-8.067	0.0000
β_1 (Number of filtering)	0.1175	0.495	0.6218
β_2 (Number of viewing pages)	0.1418	4.894	0.0000
β_3 (Average time of viewing each page)	0.0015	0.594	0.5525
β_4 (Number of viewing product pages)	0.2431	2.009	0.0445
β_5 (Average time of viewing each product page)	-0.0132	-1.446	0.1481
β_6 (Number of viewing "Study" pages)	-0.1629	-0.010	0.9922
β_7 (Number of viewing "Topic" pages)	0.6643	0.000	0.9999

It can be seen from table 5 that except β_3 and β_5 , all the other parameters are not significant, which means that for consumers who click on the email advertising to enter the website, only the number of viewing pages and product pages are influential to purchase intention. Therefore, the resulting model is as equation (6):

$$h\left(Y^{EMA}\right)=\left[1+\exp\left(-4.7250+0.1418x_2+0.2431x_4\right)\right]^{-1} \tag{6}$$

Both number of viewing pages and product pages (0.1418: 0.2431) are positive, which means that consumers will be more likely to purchase while browsing more pages, and the impact of the later than the former. Here, we consider that customers who click on an e-mail advertising link to enter the site often click the advertising caused by their interests to merchant activities or specific product information. And based on their past experience of using the website, they prefer to check specific products. As a result, the increase of viewing pages is mainly caused by product pages. In other words, an increase in product page views means that consumers are increasingly interested in the content of the e-mail advertising links, and the likelihood of their purchase conversion rises.

In general, the impact of consumers' visit behavior on purchase conversion depends on whether the behavior can increase the probability that consumers will find the product that meets his expectation. The higher the probability, the more likely to make a purchase. For enterprises, the above purchase conversion mechanisms can provide some advice for the website design and function adjustment. For example, in the real-time recommendation and coupon distribution, if a consumer clicks through an email advertising, the mangers can set an appropriate amount of coupons to promote the deal when the browsing time exceeds a certain threshold.

5. CONCLUSION

In order to explore short-term effects of online advertising further, we start from the perspective of purchase conversion to consider and use Web log data provided by a third-party insurance agency platform in Nanjing to attempt our proposed models. We first analyze short-term effects of three types of online advertising - paid search, short message service and e-mail advertising in an overall level. Besides, we put forward purchase conversion mechanisms of each online advertising to analyze the influence of consumers' behavior on purchase intention for consumers from different advertising resources. Our results help enterprises obtain marketing implications for consumers from different advertising sources. Due to the limited data provided by the platform, we only discussed short-term effects of three types online advertising. As the type of online advertising evolves, more types of online advertising may be considered in the future. And following study can extent our model, add more detailed description of the consumers' behavior characteristics to support enterprises making marketing strategy decisions.

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