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Abstract: Faced with various online ads, firms are hard to choose the most appropriate advertising channels which have best advertising effects. Online advertising has immediate and carry-over effects. We constructed a comprehensive evaluation model of multi-channel online advertising effects which can evaluate not only immediate effect but also carry-over effect based on lag effect factors. Then, we conducted a restricted grid search and multiple linear regressions to estimate the immediate effect and carry-over effect of paid search ads, mobile phone message ads and e-mail ads based on user behavior data and transaction data of an e-commerce website. The results show that the immediate effect intensity of paid-search ads is the highest, the carry-over effect duration of e-mail ads is the longest, and the cumulative carry-over effect intensity of e-mail ads is the highest. This study puts forward suggestions on how to evaluate the effects of multi-channel online ads more accurately, which can guide this e-commerce website to make better advertising strategy for online marketing.

Keywords: online ads, carry-over effect, immediate effect, advertising effect evaluation, multi-channel

1. INTRODUCTION

With the development of China's online advertising market, more and more online advertising channels have appeared, including user-initiated advertising channels(UIACs) and firm-initiated advertising channels(FIACs) shown in Figure 1. UIACs, such as search engines, are triggered by users' actions. Conversely, FIACs, such as mobile phone messages and e-mail, focus on pushing the message to the user. Different online advertising channels play different role on attracting consumers to purchase[1]. Multi-channel online ads have become an important online marketing tool for e-commerce firms. Multi-channel online ads is a kind of advertising operation pattern, which make use of banners, text links, multimedia to attract Internet users (including mobile users) in a variety of online channels. Faced with multi-channel online ads and limited advertising budget, firms need to evaluate the advertising effects to decide which channel is worth advertising.

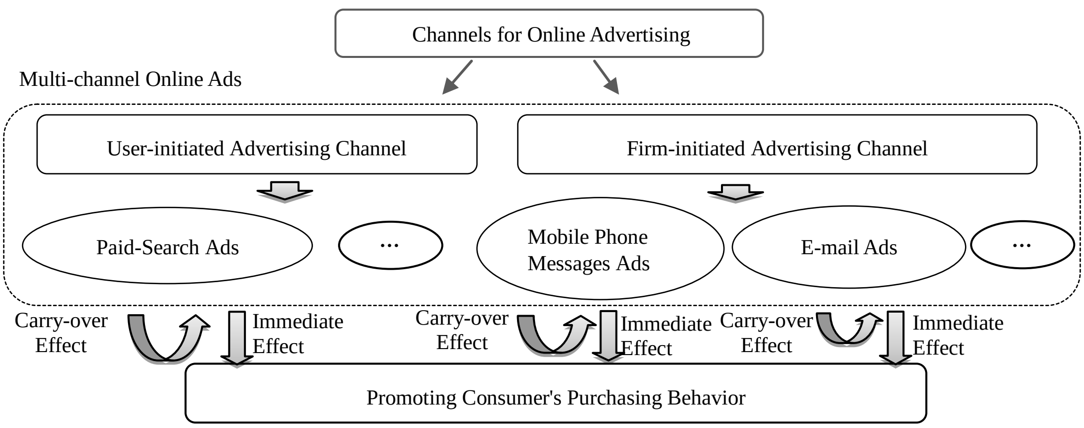

Figure 1. Online advertising channels and advertising effects

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Online advertising has many kinds of advertising effects[2], including immediate effect and carry-over effect. The immediate effect is defined as the impact of advertising on consumer behavior (such as clicking, buying, etc.) in a short period of time after the advertising displaying[3], while the carry-over effect refers to a long term advertising impact on consumer behavior[2]. However, in the existing research, most scholars only evaluate the immediate effect of online ads by measuring click-through rate or conversion rate to assess advertising effects, without considering the widespread carry-over effect of online advertising[4]. Immediate effect can only reflect the short-term impact of online advertising, ignoring the continuous impact of online advertising on user behavior. Managers may tend to be short-sighted in choosing the channel of online advertising if they just pay attention to the immediate effect evaluation results. Besides, only considering the carry-over effects will also make the effects of online ads underestimated. Therefore, in order to obtain more accurate evaluation results, it is necessary to conduct a comprehensive evaluation of the immediate effects and carry-over effects of multi-channel online ads.

In the previous research of carry-over effect evaluation, one part of studies focus on evaluating the impact intensity of the carryover effect which is accumulated over time and reflects the influence of advertisements over a period of time[5]. The other part only focuses on the duration of the carry-over effect[6][7], but without measuring the impact intensity within the duration. In fact, in order to decide the spending and timing of online advertising, it is necessary to consider both the accumulated intensity and the duration of online ads channels.

Therefore, we address the following question: What are the immediate and carry-over effects of different online advertising channels on sales? Which online advertising channel takes the longest time to create buying behavior? What’s the cumulative intensity of carry-over effect of different online advertising channels?

We develop hypotheses and test them based on the user behavior data and transaction data of a B2C e-commerce platform. Next we construct an evaluation model which can measure the impact intensity and duration of advertising effects. Then we describe the data and show the results. Lastly, we conclude by outlining the implications of our findings, the limitations of the study, and opportunities for further research.

2. RELATED LITERATURE

2.1 Evaluation of immediate effect

Many firms usually analyze the effect of online ads through click-through rate and purchase conversion rate which only reflect the immediate effect of online ads[8]. Previous research that evaluated the immediate effect of online ads based on click behavior only considered whether the online ads can attract users to click, but ignores the purchasing behavior after click[9][10]. Some other studies used the purchase conversion rate to measure the short-term effect of online ads. Purchase conversion rate refers to the proportion of users who generate purchasing behavior among the users who click on advertisements. This indicator can directly reflect the immediate impact of online ads on click-on users’ purchasing behavior. Moe uses click stream data to predict purchase conversion rate based on users’ historical purchase records[11]. Rutz et al. develops a two-stage click-to-transform model based on Bayesian model and considers consumer heterogeneity to evaluate the effectiveness of online ads[3]. Montgomery et al.[12] used dynamic multi-probit model to model users’ behavior data, and used click-stream data of an online bookstore to verify and predict the purchase conversion rate.

Most of the research reviewed on online advertising effectiveness has focused on the short-term effect of an ad campaign without taking the long-term effect into account. However, online advertising sometimes does not immediately trigger user behavior, but first forms an impression that influences later purchases. It is difficult to accurately measure the impact of online advertising in a period of time by only measuring the immediate effect.

2.2 Evaluation of carry-over effect

Some studies have shown that carry-over effect of online advertising exists widely. Carry-over advertising effect refers to the advertising impact on consumer behavior and even sales after a certain time lag [13]. Existing research shows that the carry-over effect of online ads varies with the channels of advertising. Early research on measurement of advertising carry-over effects paid more attention on the duration of advertising impact[6]. Herrington et al.[7] found that the influence of regional advertisements lasts longer than that of national advertisements. Besides the duration of advertising effects, some other authors usually used dynamic linear models to measure the accumulated impact intensity of advertising. Haan et al.[5] applied vector auto-regression and impulse response analysis to process user behavior data and estimated the carry-over effects of two kinds of ads. They found that the accumulated advertising intensity of content-aggregated ads was stronger than content-separated ads.

Collectively, although existing studies have assessed the immediate effect or the carry-over effect, there is a lack of comprehensive evaluation of these two kinds of online advertising effects. With the overall consideration of the duration and intensity of immediate effect and carry-over effect, the evaluation results can fully reflect the different effects of online advertising over time[14], and help firms to choose appropriate channels for online advertising. Therefore, this study will construct a multi-channel online advertising effect evaluation model to measure both immediate effect and the duration and cumulative intensity of carry-over effect.

3. HYPOTHESIS

To evaluate both the immediate effect and the carry-over effect of multi-channel online advertising, we address three online advertising channels in our analysis: paid-search ads, mobile phone messages ads and e-mail ads. Paid-search advertisements on search engines are on-demand advertisements based on users' search requests, which are less intrusive and not easy to arouse users' disgust. By contrast, mobile phone messages ads and e-mail ads, as kind of firm-initiated advertising, are pushed by firms. They not only have low cost, but also can be unlimited duplicated and widely diffused.

Research has shown that user's information needs, user's involvement and the attitude towards advertising can influence immediate advertising effects[15]. Users are highly involved when they actively search for the information they need and the following paid-search ads are relevant to users' demand. However, consumers passively accept e-mail ads and mobile phone messages ads which may be annoying and not really needed. The information obtained by users through their own search behavior should be more credible and persuasive than that obtained by third-party push. Compared with the firm-initiated advertising, the user-initiated advertising is more likely to meet user's demand and lead to buying in a short time. Therefore, we hypothesis that:

H1a: E-mail ads have a relatively weaker and positive immediate effect.

H1b: Mobile phone messages ads have a relatively weaker and positive immediate effect.

H1c: Paid-search ads have relatively stronger and positive immediate effect.

According to Vakratsas and Ma's[16] research, the different long-term effects of advertising channels can be attributed to two factors: the lifespan and content of advertising information.

In terms of the lifespan of advertising information, e-mail ads and mobile phone messages ads usually have a longer lifespan than paid-search ads, which can be stored in e-mail and mobile devices and be repeatedly accessed even after a long time. Comparing e-mail ads with mobile phone messages ads, the former can be stored in mobile and PC, while the latter can only be stored in mobile devices, so e-mail ads have a greater possibility of repetitive exposure. However, the paid-search advertisement is hard to be contacted repeatedly because the content presented by search engines is not static. Therefore, the following assumptions can be made:

H2a: E-mail ads have the longest carry-over effect of the three advertising channels.

H2b: Mobile phone messages ads have shorter carry-over effect than e-mail ads and longer than paid-search ads.

H2c: Paid-search ads have the shortest carry-over effect of the three advertising channels.

In fact, the cumulative impact intensity of advertising carry-over effect needs to consider both the immediate effect and the duration of advertising carry-over effect. In view of users' information needs and the information lifespan, we assumed that mobile phone messages ads have weaker carry-over effect intensity than the other two advertising channels. In addition, from the perspective of advertising information content, Some research reveals that rich advertising content has positive impact on users [17]. Paid-search ads and mobile phone messages ads are usually presented in the form of text and links restricted by search engine typesetting, investment funds and mobile screen. E-mail ads don't have so many restrictions and the content is more of variety, usually with pictures to enrich the advertisement content and enhance attraction. Thus, according to the discussion in the three aspects, we hypothesis that:

H3a: E-mail ads have the strongest cumulative carry-over effect of the three advertising channels.

H3b: Paid-search ads have a weaker cumulative carry-over effect than e-mail ads and stronger than mobile phone messages ads.

H3c: Mobile phone messages ads have the weakest cumulative carry-over effect of the three advertising channels.

4. RESEARCH METHOD

In order to explore and compare the immediate effect and carry-over effect of different online advertising channels, we construct an effect evaluation model of different online advertising channels based on the direct aggregation approach[1] and shown in model (1):

$$S_t=\beta_0+\beta_1 x^*_{1t}+\beta_2 x^*_{2t}+\beta_3 x^*_{3t}+\varepsilon_t \tag{1}$$

where x^*_{1t}, x^*_{2t}, x^*_{3t} respectively capture the online advertising click stock of the paid-search ads, mobile phone messages ads and the e-mail ads on day t. And the coefficient β_1, β_2, β_3 respectively refer to the immediate effect of paid-search ads channels, mobile phone messages ads channels and e-mail ads channels, taking into account the carry-over effects. S_t is the sales volume of day t. Given that the online advertising click stock on day t (x^*_{it}) probably can be affected by previous clicking and browsing behavior of the day before, x^*_{it} is built recursively in the following manner:

$$\begin{gathered} x^*_{i1}=x_{i1} \\ x^*_{i2}=(1\text{-}\lambda_i)x_{i2}+\lambda_i x^*_{i1} \\ x^*_{i3}=(1\text{-}\lambda_i)x_{i3}+\lambda_i x^*_{i2} \\ \cdots\cdots \\ x^*_{it}=(1\text{-}\lambda_i)x_{it}+\lambda_i x^*_{i,t-1} \end{gathered} \tag{2}$$

where x_{it} captures the number of clicks on the online advertising channel i (i =1,for paid-search ads; i =2, for mobile phone messages ads; and i=3, for e-mail ads) on day t. The lag effect factors of different online advertising channels is denoted by λ_i which are used to reflect the carry-over effect[1].

To estimate the parameters of the model, including the immediate effect values (β_1, β_2, β_3) and the lag effect factors of the three channels(λ_1, λ_2, λ_3), we firstly used the method of restricted grid search in increments of 0.05 within a range of 0< λ < 1 to find the values of λ that minimize the residual sum of squares(RSS). Specifically, we used 19 different values of λ of each online advertising channel to calculate the online advertising click stock(x^*_{it}) of each channel. Then we can obtain 6859 combinations of different values of λ_i. Therefore, model (1) was run 6859 times, calculating the corresponding residual sum of squares of each time to find the optimal combinations of different values of λ_i (λ^*_1, λ^*_2, λ^*_3), which minimizes RSS. The optimal combinations of λ^*_i is used to calculate the optimal online advertising click stock x^*_{it} through the formula (2). Finally, the immediate advertising effects (β_1, β_2, β_3) are estimated using ordinary least squares(OLS) regression by inserting the optimal online advertising click stock (x^*_{it}) into model(1).

5. EMPIRICAL RESEARCH

5.1 The data

We cooperated with an E-Commerce firm in Nanjing of China to obtain empirical data. The consumers can browse, consult and purchase various products on their website. In order to improve the brand recognition and expand their product sales, the firm mainly guides consumers to the website by external advertising. Our data is collected from the log data of the firm's websites that tracks the daily user's accessing behavior. Each visit to the website is recorded and stored in the firm's log database with *User IP*, *Access Time Stamp*, *Access Date*, *Access Source*, *Access Request*, *User Agent*, *User Cookies*, *URL of websites* and so on.

We firstly collected 9,209,079 log data as original data using a time span of 90 days (from 01/01/2017 to 03/31/2017). Then, we delete some dirty data like spider and abnormal access records. To track each user's advertising clicking path and purchase behavior, we need to do user identification and session partitioning first. We mainly used cookies to identify unique user. If there is no cookie, we used IP, and *User Agent* (recording the type of the device and browser the user is accessing) to identify individual. Then, we can extract the behavior characteristics of each user in a single session. The behavioral characteristic variables generally include the number of ad clicks and the purchase conversions volume of the three channels. We can know which advertising channel the user is coming from by *Access Source* in the log data. And when visiting a web page, if the keyword "confirm" appears in the URL of the web page, it means that he/she has entered the order confirmation page and finished the purchase. So we use this URL to extract the purchase conversions volume from the database. Finally, we consolidated the behavior characteristics data records for three channels in time sequence into one basic data set with a total of 355241 pieces of data.

However, we find that the data set is unbalanced. The proportion of data records having purchasing behavior is very small, which is only 2% of all data records. The proportion of non-purchasing is much larger than purchasing. Obviously, it's likely to cause deviation when directly using this imbalanced data set to perform a regression. To solve the problem of the unbalanced large-scale binary data (buy/not buy), Lu, Jerath and Singh[19] proposed that a large number of non-purchase data can be randomly sampled to construct a new sample set for model estimation, which can not only reduce the estimation time, but also obtain accurate estimation of parameter. Therefore, we used this method to re-sample our data by extracting all the data that have purchasing and randomly extracting 10% of the data records that have no purchasing. A new sample data set is constructed, including 34,736 users that do not have purchase behavior and 7881 users that have.

Lastly, by summing up the daily advertising clicks and purchase volume of each user on each advertising channel, we obtained the time series data of advertising clicks(x_i) and purchase volume(S_t) on the three advertising channels for modeling shown in Table 1.

Table 1. Time series data set of user behavior characteristics

time	x_1	x_2	x_3	S_t
2017-01-18	705	3	2	315
2017-01-19	630	4	3	301
……	……	……	……	……
2017-03-31	1005	0	2	221

5.2 Research results

Due to the influence of the distribution of advertising resources and advertising policy, the daily visits of the three advertising channels are not balanced, and the daily visits of the paid-search channel have the different magnitude from the other two channels. In order to improve the curve fitting effect of multi-dimensional data of different magnitude, we standardized the data between 0 and 1 with the equation (3) specified as below:

$$x^{**}=\frac{x\text{-}min}{max\text{-}min} \tag{3}$$

where x^{**} is the normalized value, max is the maximum value in the sample and min refers to the minimum in the sample. Then we used this standardized data to run the restricted grid search.

As shown in Table 2, by means of restricted grid search, we found the optimal combinations of different values of λ_i (λ^*_1) that has the minimum value of RSS(about 2.03565).

Table 2. Optimal lag effect factors λ_i^* of multi-channel online advertising

Parameter	*Optimal λ value*	*Standard error*	*Minimum standardized residuals*	*Minimum RSS*
λ_1^*(Paid-search ads)	0.05	0.064***	0.153851732459254	2.0356505799414
λ_2^*(Mobile phone messages ads)	0.35	0.122**		
λ_3^* (E-mail ads)	0.55	0.112**		

Note: * p<.10, ** p<.05, *** p<.01

It can be seen in the Table 2 that e-mail ads have the largest value ($\lambda_3^* = 0.55$) of optimal lag effect factor in the three advertising channels, followed by the mobile phone messages ads ($\lambda_2^* = 0.35$). The optimal λ value of paid-search ads ($\lambda_1^* = 0.05$) is the least. The lag effect factor λ here means the carry-over effect, which is the percentage of advertising effect that carries over from time period t to time period t+1.

After calculating the optimal advertising click stock through formula (2) based on the optimal combinations of λ_i^* mentioned above, we estimated the parameters of model (1) using OLS regression. The estimation results summarized in Table 3 show that the immediate effect of paid-search ads is strongest of the three channels with the value of 0.47, supporting Hypothesis 1c. The immediate effect of mobile phone messages ads (β_2=0.349) is slightly stronger than that of e-mail ads (β_3=0.317). E-mail ads have less influence on customers' immediate purchasing behavior than paid-search ads, and instead play a more important role in their subsequent purchasing behavior. As can be seen in Table 3, the adjusted R-square is 43.69%, which shows that the model has a good fitting effect.

Table 3. Model fitting results

Immediate effect	*β_1(Paid-search ads)*	*β_2(Mobile phone messages ads)*	*β_3(E-mail ads)*
Parameter values	0.470	0.349	0.317
Adjusted R-square	43.69%		

In order to further obtain the duration and the cumulative intensity of carry-over effect of different advertising channels, we use the methods mentioned in the research of Greene[18] as shown in below equations:

$$T = \beta / (1-\lambda) \tag{4}$$

$$t = \log(1\text{-}90\%) / \log\lambda \tag{5}$$

where T refers to the cumulative intensity of carry-over effect. t means the duration of the carry-over effect which is defined as the number of days until 90% of the carry-over effect of advertising has happened.

Finally, we estimated the immediate effect, the lag effect factor, the duration of carry-over effect and the cumulative intensity of carry-over effect as illustrated in Table 4.

Table 4. Advertising effect of multi-channel online ads

Online Advertising Channels	*Immediate effect (β_i)*	*Standard error*	*Lag effect factor (λ_i)*	*Duration of carry-over effect(days)*	*Cumulative intensity of carry-over effect*
Paid-search ads	0.470	0.064***	0.05	0.769	0.495
Mobile phone messages ads	0.349	0.122**	0.35	2.193	0.537
E-mail ads	0.317	0.112**	0.55	3.852	0.704

Note: * p<.10, ** p<.05, *** p<.01 * P < 0.10, ** P < 0.05, *** P < 0.01

Comparing the data results with the research hypothesis, we can find that:

(1) The estimation results in Table 4 support the three hypotheses of Hypotheses 1. The H1c is supported since the paid-search ads channel has the strongest immediate effect ($\beta_1 = 0.47$). The other two advertising channels both have a weaker and positive impact on consumer's currently purchasing behavior (c.f. Table 4), which supports H1a and H1b. The paid-search ads can more quickly identify and satisfy the user's needs according to the user's requests and prompt the user to purchase immediately or in a short period of time. This is why it has the strongest immediate effect in the three online advertising channels. In addition, the reason why the immediate effect of mobile phone messages ads is stronger than that of e-mail ads may be that short messages are sent directly to the customer's mobile phone, which can immediately inform people to check it. What's more, consumers can click on the short message advertising link more conveniently on the mobile phone and view more details, which can also increases the chances of consumer's purchasing.

(2) The hypothesis H2 are all supported because e-mail ads channel has the longest duration of the carry-over effect of 3.852 days, almost double of that of mobile phone messages ads (t=2.193 days) and four times of that of the paid-search ads (t=0.769). The duration of carry-over effect of paid-search ads channel is the shortest of 0.769 days, less than one day, which is consistent with the conclusion that it has the strongest immediate effect. It can be seen that paid-search ads channel is a powerful channel for immediate sales.

(3) In the hypothesis H3 about the cumulative intensity of the carry-over effect, only H3a is supported since e-mail ads have the strongest cumulative intensity of carry-over effect of all the online advertising channels analyzed, reaching 0.704. Hypothesis3b and 3c have to be rejected because it is the mobile phone messages ads channel that has the second strongest cumulative intensity of carry-over effect (about 0.537) of the three channels analyzed instead of paid-search ads whose cumulative intensity of carry-over is 0.493. The results indicate that e-mail ads channel with richer content and more diversified forms works much better to win the purchases in the long term than the other two channels. Therefore, the richness and diversity of advertising content are important factors to attract consumers to purchase. In addition, it may be because e-mail ads and mobile phone messages ads are likely to meet more needs beyond our expectation that makes the empirical results different from our hypothesis. Besides promoting all registered users with e-mail ads and mobile phone messages ads, the firm may also identify latent customers who often browse and buy products on their websites based on their historical data and push these ads to these customers inclined to buy things. In this case, e-mail ads and mobile phone messages ads can be further cater to user's demand compared with paid- search ads.

6. CONCLUSIONS

Most of the existing online advertising effect evaluation studies focus on the immediate effect evaluation using the user data obtained by the questionnaire or the overall sales and advertising data provided by the enterprise, which does not make full use of the firm's log data derived from the online ads. However, the carry-over effect of advertising differs significantly from immediate effect. For strategic brand-building purposes, firms also need a better understanding of how online ads affect consumers in the long run. Therefore, our study responds to deficiencies in these studies by conducting a comprehensive evaluation study on the immediate effect and carry-over effect of multi-channel online ads using click-stream data of users on different advertising channels. Managers and practitioners can use the approach described in this paper to analyze their own online advertising log data to determine which advertising channel has the appropriate effect on sales and improve the effectiveness of their online advertising marketing.

There are still some limitations to be further discussed and improved in the future:

(1) When evaluating the effect of multi-channel online ads, we choose to sum up the number of advertising channel clicks and purchases of a single user by the day. Further research should evaluate the advertising effects

at user's individual level for more granular analysis.

(2) This study is limited to the advertising policies of the firm we cooperate with. It only evaluates the effects of paid-search, mobile phone messages and e-mail advertising channels. With the development of social media advertising, we can evaluate the effects of social media advertising channel and make a comparison with other channels in future research.

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REFERENCES

[1] Li H, Kannan P K. (2014). Attributing conversions in a multichannel online marketing environment: an empirical model and a field experiment. Journal of Marketing Research, 51(1): 40-56.

[2] Becker I F, Linzmajer M, Wangenheim F V. (2017). Cross-industrial user channel preferences on the path to online purchase: homogeneous, heterogeneous, or mixed? Journal of Advertising, 46(2): 248-268.

[3] Rutz O J, Trusov M. (2011). Zooming in on paid search ads--a consumer-level model calibrated on aggregated data. Marketing Science, 30(5): 789-800.

[4] Liu-Thompkins Y. (2019). A decade of online advertising research: what we learned and what we need to know. Journal of Advertising, 1-13.

[5] Haan E D, Wiesel T, Pauwels K. (2016). The effectiveness of different forms of online advertising for purchase conversion in a multiple-channel attribution framework. International Journal of Research in Marketing, 33(3): 491-507.

[6] Berkowitz D, Allaway A, Apossouza G. (2001). The impact of differential lag effects on the allocation of advertising budgets across media. Journal of Advertising Research, 41(2): 27-36.

[7] Herrington J D, Dempsey W A. (2005). Comparing the current effects and carryover of national-, regional-, and local-sponsor advertising. Journal of Advertising Research, 45(01): 60-72.

[8] Wiesel T, Pauwels K, Arts J. (2011). Marketing's profit impact: Quantifying online and off-line funnel progression. Marketing Science, 30(4): 604–611.

[9] Zhang Y, Jansen B J, Spink A. (2009). Identification of factors predicting click-through in web searching using neural network analysis. Journal of the American Society for Information Science and Technology, 60(3): 557-570.

[10] Nottorf F. (2014). Modeling the clickstream across multiple online advertising channels using a binary logit with Bayesian Mixture of Normals. Electronic Commerce Research & Applications, 13(1): 45-55.

[11] Moe W W, Fader P S. (2004). Dynamic conversion behavior at E-Commerce sites. Management Science, 50(3): 326-335.

[12] Montgomery A L, Li S, Liechty S J C. (2004). Modeling online browsing and path analysis using clickstream data. Marketing Science, 23(4): 579-595.

[13] Danaher P J, Van Heerde H J. (2018). Delusion in attribution: Caveats in using attribution for multimedia budget allocation. Journal of Marketing Research, 55(5): 667-685.

[14] Barajas J, Akella R, Holtan M, et al. (2016). Experimental designs and estimation for online display advertising attribution in marketplaces. Marketing Science, 35(3): 465-483.

[15] Klapdor S, Anderl E, Schumann J H. (2015). How to use multichannel behavior to predict online conversions behavior patterns across online channels inform strategies for turning users into paying customers. Journal of Advertising Research, 55(4): 433-442.

[16] Vakratsas D, Ma Z. (2005). A look at the long-run effectiveness of multimedia advertising and its implications for budget allocation decisions. Journal of Advertising Research, 45(2): 241-254.

[17] Maity M, Dass M, Kumar P. (2018). The impact of media richness on consumer information search and choice. Journal of Business Research, 87: 36-45.

[18] Greene W H. (2007). Econometric Analysis. The sixth edition. New York: Pearson Education Inc.

[19] Lu Y, Jerath K, Singh P V. (2013). The emergence of opinion leaders in a networked online community: A dyadic model with time dynamics and a heuristic for fast estimation. Management Science, 59(8): 1783-1799.