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Social media advertisement optimization algorithm based on fuzzy set theory and its effect on purchasing behavior

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ABSTRACT

Product awareness can be spread to a wider audience through advertisements, and the introduction of social media platforms has made it easier for marketers to spread brand advertisements and fully attract consumers to generate corresponding purchasing behaviors. Based on fuzzy set theory, the article establishes a fuzzy evidence theory through evidence-weighted fusion, and calculates the utility value of social media advertisements in order to achieve the optimal evaluation of social media advertisements. Then, it explores the influence of social media advertisements on consumers' purchasing behavior with OLS-LR model, and combines the VAR model to study the dynamic correlation between different types of social media advertising channels and consumers' purchasing behavior. Without considering the control variables, the regression coefficient of social media advertising on consumer purchasing behavior is 0.438, which is significant at 1% level. With the fourth-order VAR model, CICs social media advertisements have a significant short-term effect on consumer purchasing behavior, while FICs advertisements show a long-term effect. Based on the fuzzy evidence theory, the utility value of social media advertisements can be calculated, and based on the sorting of the calculation results, the construction of optimization paths of social media advertisements can be realized, which provides a new research basis for improving the efficiency of corporate advertising and marketing.

Keywords: fuzzy set theory, evidence-weighted fusion, OLS-LR model, VAR model, social media advertising, purchasing behavior

1. Introduction

In the Internet era, social media has become an integral part of people's lives. With the rapid development of social media, many enterprises have begun to pay attention to social media as a channel for advertising promotion. Social media advertising refers to a form of advertising that is pushed to specific target groups through social media platforms [1-4]. Compared with traditional

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advertisements, social media advertisements are characterized by relevance, diversity of forms, interactivity, etc. With the introduction of social media advertisements, consumer behavior has also changed [5-7].

In the past, brand marketing mainly relies on advertising channels, such as TV ads, newspaper ads and so on. However, the cost of these advertising channels is high and the effect is difficult to evaluate. With the rise of social media, brands begin to utilize social media platforms for publicity and communication, which is less costly and more effective [8-11]. Through social media, brands can create different and more personalized promotional methods to attract more target consumers. In addition, through social media platforms, brands are able to obtain consumers' feedback on their products and services in a timely manner, which can help brands make corrections and improvements [12-15]. And use a variety of ways to stimulate consumer behavior, however, consumers also need to be rational and vigilant in the use of social media, not to be influenced by blind promotion and comparison psychology. Only after clarifying their needs and goals can they really make wise purchase decisions [16-19].

In this high-tech world where social media is at your fingertips, how to optimize the delivery of social media advertisements and enhance the attractiveness of social media advertisements to consumers has become a must-consider issue for enterprises to improve their marketing effectiveness. The article takes the consumer data of a certain treasure as the research sample, and crawls the related research data through Python technology. The fuzzy set theory and DS evidence theory are combined to construct a fuzzy evidence theory for social media advertising optimization. In order to study the influence of social media advertisements on consumers' purchasing behavior, the degree of influence of social media advertisements is explored through OLS-LR model, and the dynamic trend of different types of social media advertisement channels on consumers' purchasing behavior is explored by combining with VAR model.

2. Social media advertising optimization model

With the development of the Internet, social media and especially mobile media technology, media is no longer monopolized by professional organizations, information is no longer limited by geography, and information sharing has become easy and large-scale. Such a big shift continues to affect the whole society, but also affect the behavioral orientation of advertising and marketing. Relying on social media advertising can promote the enhancement of enterprise marketing effect, but also can maximize the attraction of consumers to implement the purchase behavior, how to achieve the optimization of social media advertising has become an important method to assist enterprises to carry out marketing strategy.

2.1. Fuzzy set theory and DS evidence theory

2.1.1. Fuzzy set theory. Fuzzy set theory contains fuzzy numbers, fuzzy operations and decomposition principles, which are the basis for the application of fuzzy set theory to practical problems, as follows:

1) Fuzzy numbers. Let S be a fuzzy set in the domain of real numbers $\mathbb{R}$. A fuzzy number is said to be S when it satisfies that S is a regular fuzzy set, S is a convex set as well as S is bounded and all $\alpha-$intercepts are closed intervals in $\mathbb{R}$ and the global domain of a fuzzy number is its 0-intercept [20].

2) Fuzzy operations. Let S and T be two fuzzy numbers and their $\alpha-$intercept sets are $S_\alpha=[s_\alpha^-,s_\alpha^+]$, $S_\alpha=[t_\alpha^-,t_\alpha^+]$, $\alpha\in[0,1]$. The operation of addition, subtraction, multiplication and division between two fuzzy numbers S and T is defined as:

$$(S+T)_\alpha=[s_\alpha^-+t_\alpha^-,s_\alpha^++t_\alpha^+], \tag{1}$$

$$(\mathrm{S}-\mathrm{T})_{\alpha}=[\min(\mathrm{s}_{\alpha}^{-}-\mathrm{t}_{\alpha}^{-},\mathrm{s}_{\alpha}^{+}-\mathrm{s}_{\alpha}^{+}),\max(\mathrm{s}_{\alpha}^{-}-\mathrm{t}_{\alpha}^{-},\mathrm{t}_{\alpha}^{+}-\mathrm{t}_{\alpha}^{+})] \tag{2}$$

$$(\mathrm{S}\cdot\mathrm{T})_{\alpha}=[\min(\mathrm{s}_{\alpha}^{-}\mathrm{t}_{\alpha}^{-},\mathrm{s}_{\alpha}^{-}\mathrm{t}_{\alpha}^{+},\mathrm{s}_{\alpha}^{+}\mathrm{t}_{\alpha}^{-},\mathrm{s}_{\alpha}^{+}\mathrm{t}_{\alpha}^{+}),\max(\mathrm{s}_{\alpha}^{-}\mathrm{t}_{\alpha}^{-},\mathrm{s}_{\alpha}^{-}\mathrm{t}_{\alpha}^{+},\mathrm{s}_{\alpha}^{+}\mathrm{t}_{\alpha}^{-},\mathrm{s}_{\alpha}^{+}\mathrm{t}_{\alpha}^{+})] \tag{3}$$

$$(\mathrm{S}/\mathrm{T})_{\alpha}=[\min(\mathrm{s}_{\alpha}^{-}/\mathrm{t}_{\alpha}^{-},\mathrm{s}_{\alpha}^{-}/\mathrm{t}_{\alpha}^{+},\mathrm{s}_{\alpha}^{+}/\mathrm{t}_{\alpha}^{-},\mathrm{s}_{\alpha}^{+}/\mathrm{t}_{\alpha}^{+}),\max(\mathrm{s}_{\alpha}^{-}/\mathrm{t}_{\alpha}^{-},\mathrm{s}_{\alpha}^{-}/\mathrm{t}_{\alpha}^{+},\mathrm{s}_{\alpha}^{+}/\mathrm{t}_{\alpha}^{-},\mathrm{s}_{\alpha}^{+}/\mathrm{t}_{\alpha}^{+})] \tag{4}$$

3) Decomposition principle. Define a fuzzy set $\hat{S}_{\alpha}$ in U which has an affiliation function:

$$\varpi_{\hat{S}_{\alpha}}=\alpha I_{S_{\alpha}}(x) \tag{5}$$

$I_{S_{\alpha}}(x)=1$ when $x\in S_{\alpha}$ and $I_{S_{\alpha}}(x)=0$ when $x\in \mathrm{U}-S_{\alpha}$, then for fuzzy set S can be obtained:

$$S=\bigcup_{\alpha\in[0,1]}\hat{S}_{\alpha} \tag{6}$$

where $\bigcup$ is the union set of fuzzy sets, and after performing fuzzy operations on two fuzzy numbers through $\alpha-$ truncated sets, the decomposition theorem can be applied to construct the resulting fuzzy number's affiliation function.

A fuzzy set can be represented by a set of numbers (Ω,ϖ), where Ω is a non-empty reference set known as the global domain. The value for any $\mathrm{T}\in\Omega,\varpi(\overline{2})$ is known as the affiliation of the null in (Ω,ϖ) and the function $\varpi=\mu_{S}$ is known as the affiliation function of the fuzzy set $S=(\Omega,\varpi)$.

In fuzzy set $S=(\Omega,\varpi)$, for each $\nu\in\Omega$, its affiliation function is given by $\varpi(\nu)=\mu_{S}$. The relationship between element $\nu\in\Omega$ and fuzzy set S is:

When $\varpi(\nu)=0$, ν does not belong to fuzzy set S. when $\varpi(\nu)=1$, ν all belong to fuzzy set S. when $0<\varpi(\nu)<1$, ν partially belong to fuzzy set S.

There are many forms of the affiliation function, the common ones are Gaussian, bell, trapezoidal, triangular, etc., and there are some differences in the scope of application of different affiliation functions.

2.1.2. DS Theory of Evidence. D-S Evidence Theory is a method for uncertain reasoning and decision making using evidence credibility distribution functions and Dempster's synthesis rule. The method enables the fusion of information from multiple sources when the evidence comes from n independent and different sources of hypotheses [21].

Suppose Θ is given an identification framework, and if the mass function $2^{\Theta}\to[0,1]$ satisfies the following equation, then call m the basic credibility assignment function on the identification framework Θ. For any $A\subseteq\Theta,m(A)$ is called the basic credibility of A, denoting the degree to which the evidence supports the occurrence of proposition A. The set consisting of all focal elements under the identification frame Θ is called the power set of Θ, denoted as 2^{Θ}. i.e:

$$\begin{cases} m(\varnothing)=0 \\ \sum\limits_{j\subseteq\Theta} m(A)=0 \end{cases} \tag{7}$$

where A is a subset of Θ and $m(A)>0$, A are called the focal elements of the evidence.

Dempster's synthesis rule produces more reliable evidence information by combining independent evidence from different information sources. Assuming that there are n reliable bodies of evidence under the same identification framework, $E_1,E_2,\cdots,E_n,m_1,m_2,\cdots,m_n$ are the corresponding basic trust allocation functions, and the number of joules is N, i.e., $A_j(j=1,2,\cdots N)$. When $0<K=\sum\limits_{\cap A_i=A} m_1(A_1)m_2(A_2)\cdots\cdots m_n(A_N)<1$, the D-S evidence theory combination rule can be defined as:

$$m(A)=\begin{cases}\dfrac{\sum\limits_{\cap A_j=A}\prod\limits_{i\in n} m_j(A_j)}{1-K} & A\neq\varnothing\\ 0 & A=\varnothing\end{cases} \tag{8}$$

where $\frac{1}{1-K}$ is the normalization factor, K is the conflict coefficient, which describes the conflict information between two different pieces of evidence, and at $K=1$, it indicates a complete conflict between the pieces of evidence.

2.2. Social Media Advertising Optimization Process

2.2.1. Weighted fusion of evidence. Weighted fusion is able to obtain modified evidence by weighting the original evidence, which is based on the principle of finding the similar parts of the fusion results by mathematically deforming the fusion process to arrive at the definition of a uniform trust allocation mechanism. Let the identification framework be $\Theta=(A_1,A_2)$, m_1 and m_2 are the basic probability assignments (BPAs) of the two pieces of evidence, respectively. $m_1(A_1)=a, m_1(A_2)=b; m_2(A_1)=c, m_2(A_2)=d$. where a,b,c,d are both greater than 0 and $a+b=1$, $c+d=1$. If the weights of the two pieces of evidence are known to be ω_1 and $\omega_2(\omega_1+\omega_2=1)$, the following combination of evidence can be expressed as:

$$\begin{cases}m(A_1)=\omega_1 a+\omega_2 c\\ m(A_2)=\omega_1 b+\omega_2 d\end{cases} \tag{9}$$

The two pieces of evidence are obtained by morphing them according to their BPA relationship:

$$\begin{cases}m(A_1)=\omega_1 a(c+d)+\omega_2 c(a+b)\\ m(A_2)=\omega_1 b(c+d)+\omega_2 d(a+b)\end{cases} \tag{10}$$

$$\begin{cases}m(A_1)=(\omega_1+\omega_2)ac+\omega_1 ad+\omega_2 cb\\ m(A_2)=(\omega_1+\omega_2)bd+\omega_1 bc+\omega_2 da\end{cases} \tag{11}$$

According to $\omega_1+\omega_2=1$, the above equation is further deformed to obtain:

$$\begin{cases}m(A_1)=ac+\dfrac{\omega_1 ad}{\omega_1+\omega_2}+\dfrac{\omega_2 cb}{\omega_1+\omega_2}\\ m(A_2)=bd+\dfrac{\omega_1 bd}{\omega_1+\omega_2}+\dfrac{\omega_2 ad}{\omega_1+\omega_2}\end{cases} \tag{12}$$

From Eq. (12) it can be seen that the result of weighted fusion translates into the result of conflict allocation, where conflicts are allocated proportionally to known weights:

$$\begin{cases}m(A_1)=a\left(\dfrac{\omega_1 d}{\omega_1+\omega_2}+\dfrac{c}{2}\right)+c\left(\dfrac{\omega_2 b}{\omega_1+\omega_2}+\dfrac{a}{2}\right)\\ m(A_2)=b\left(\dfrac{\omega_1 c}{\omega_1+\omega_2}+\dfrac{d}{2}\right)+d\left(\dfrac{\omega_2 a}{\omega_1+\omega_2}+\dfrac{b}{2}\right)\end{cases} \tag{13}$$

From equation (13), it can be seen that the conflict distribution is once again transformed into the form of weighted fusion, if the weight of each BPA is called the respective gained trust, the trust gained by the four BPAs is not necessarily equal to the previous weight ω_1 and ω_2, but the mathematical deformation does not affect the fusion results, based on the above idea, the combination of the conflict proportion distribution is used to combine the methods of the combination of the results of the m_1

and m_2 are:

$$\begin{cases} m(A_1) = ac + \dfrac{p(a)ad}{p(a)+p(d)} + \dfrac{p(c)cb}{p(c)+p(b)} \\ m(A_2) = bd + \dfrac{p(b)bc}{p(b)+p(c)} + \dfrac{p(d)da}{p(d)+p(a)} \end{cases} \tag{14}$$

where $p(\cdot)$ denotes the proportion of conflicting distributions and the sum of the ratios of a pair of conflicting distributions is 1. Then:

$$\begin{cases} m(A_1) = a\left(\dfrac{p(a)ad}{p(a)+p(d)} + \dfrac{c}{2}\right) + c\left(\dfrac{p(c)cb}{p(c)+p(b)} + \dfrac{a}{2}\right) \\ m(A_2) = b\left(\dfrac{p(b)bc}{p(b)+p(c)} + \dfrac{d}{2}\right) + d\left(\dfrac{p(d)da}{p(d)+p(a)} + \dfrac{b}{2}\right) \end{cases} \tag{15}$$

Comparing Eq. (13) and Eq. (15), it can be seen that the conflict proportion distribution is similar to the weighted fusion method, and the analysis of the trust distribution method can be obtained by obtaining the trust value from $BPA\alpha$, for example:

$$\begin{cases} \dfrac{p(a)d}{p(a)+p(d)} + \dfrac{c}{2} = d \times \dfrac{p(a)}{p(a)+p(d)} + c \times \dfrac{1}{2} \\ \dfrac{\omega_1 d}{\omega_1 + \omega_2} + \dfrac{c}{2} = d \times \dfrac{\omega_1}{\omega_1 + \omega_2} + c \times \dfrac{1}{2} \end{cases} \tag{16}$$

From Eq. (16), it can be seen that the trust obtained by $BPAa$ comes from two parts, one part is $BPAd$ and the other part Eq. $BPAc$. c and a support the same part, and d and a constitute the conflict part.

Based on the above analysis, this paper gives the expression paradigm of the unified trust allocation formula, i.e.:

$$\omega_{i1} = \sum_{m=2}^{n} (P_m \times m_j(A_m)) + \frac{1}{2} \times m_j(A_1) \tag{17}$$

where P_m is the trust ratio of $m_j(A_m)$. The trust allocation ratio between BPAs supporting the unified proposition can be set according to the actual situation, so extending the above equation can be obtained:

$$\omega_{i1} = \sum_{m=2}^{n} (P_m \times m_j(A_m)) + P_1 \times m_j(A_1) \tag{18}$$

where P_1 is the trust ratio of $m_j(A_1)$. From the above equation, it can be seen that the unified trust allocation formula is consistent with the unified trust allocation mechanism. The treatment of the conflict part of the unified trust allocation formula is consistent with the two improvement ideas, but the treatment of the non-conflict part is inconsistent.

2.2.2. Fuzzy Evidence Advertising Optimization. Based on the previous analysis about fuzzy set theory and DS evidence theory, this paper proposes a social media advertisement optimization evaluation algorithm based on weighted evidence fusion of fuzzy set theory, which is applicable to the situation where there are more evidence and multiple types of opinions exist simultaneously. Figure 1 shows the optimization evaluation algorithm of social media advertisement based on fuzzy evidence theory, and the basic application idea is to calculate the weight of each type of opinion first, and then calculate the weight of each piece of evidence, and finally arrive at the probability of different social media advertisements occurring [22].

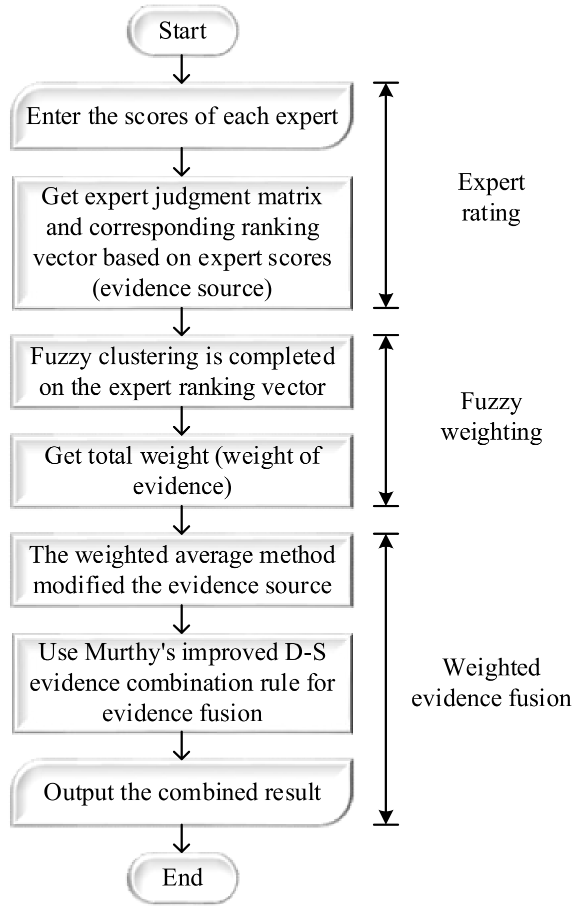


Fig. 1. Fuzzy evidence advertising optimization process

The specific steps are as follows:

1) Scoring social media advertisements. According to the actual project to establish the corresponding evaluation index system and identification framework, and expert scoring and get the corresponding preference matrix, so as to get its sorting vector.

2) Expert evidence fuzzy clustering assignment. First complete the clustering of the sorting vector, iteratively obtain the final clustering results and calculate the weighted evidence weights to reduce the impact of unreliable evidence information on the synthesis results.

3) Calculate the grade of each index based on DS evidence theory. Based on the expert weights derived from the fuzzy sets, the evidence sources are processed, and then the final grades are calculated based on the synthesis law of DS evidence theory, which in turn completes the output of the optimization results of social media advertisements.

2.3. Social Media Advertising Optimization Analysis

2.3.1. Data collection and pre-processing. In this paper, we collect the advertisement data of major e-commerce apps from 2022 to 2023 by using Python's own crawler technology, and code the information of advertisement goods such as category, attribute, brand, sales, price, number of times of collection, number of times of display, and also code for user and store details.

In this paper, the treatment of missing data, if the data is missing more, delete, and vice versa, the data is missing less, fill in the supplement with the average or the plurality. In order to eliminate the influence of the indexes, it is necessary to standardize the data, limit the data to a certain interval, the indicators are in the same order of magnitude, so that the indicators are comparable to each other, and the calculation is more convenient and suitable for comprehensive comparative evaluation. This paper mainly uses linear normalization for data standardization, i.e.:

Linear normalization is a linear change in the original data, mapping the data values to between [0,1] and. Then:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{19}$$

Difference normalization preserves the relationships that existed in the original data and is the simplest method of eliminating the effects of magnitude and range of data values.

2.3.2. Social Media Advertising Optimization Results. This paper focuses on the optimization decision analysis of social media advertisements established in the advertisement image of social media APP, which mainly focuses on the advertisement content (T1), commodity price (T2), word-of-mouth (T3), advertisement design (T4), advertisement push (T5), and the perceived risk (T6) as the evaluation indexes, and divides the attribute importance expectancy value by 10 experts. The expected value of attribute importance is divided into five levels, which take the values of 0.05, 0.25, 0.5, 0.75, and 0.95, which results in the average fuzzy weight of each attribute of 0.591, 0.614, 0.535, 0.647, 0.415, and 0.493, respectively.

Assuming that a consumer has clearly defined the purchase demand and plans to buy a dress on a certain treasure app, through a lot of browsing, he/she finally locks 10 commodity ads (X1~X10) from which he/she will make a choice among these 10 commodities. The 10 commodity advertisements are analyzed and evaluated based on the advertisement content (T1), commodity price (T2), word-of-mouth (T3), advertisement design (T4), advertisement push (T5), and perceived risk (T6), which help consumers determine the commodity with the optimal utility value. The evaluation process of social media ad optimization based on fuzzy evidence is as follows:

1) Data preprocessing. Construct the decision matrix of consumers' alternative commodity advertisements, and qualitatively transform them through Gaussian affiliation function for quantitative values, and then obtain the normalized decision matrix. All attribute values are converted into corresponding fuzzy sets according to the affiliation function, and the converted attribute evaluation value matrix is obtained as shown in Table 1. Where g1~g5 represent the worst, worse, average, better and best respectively.

Table 1. The converted attribute evaluation matrix

Advertise	Attribute					
	T1	T2	T3	T4	T5	T6
X1	{(g2,0.5),(g1,0.5)}	{(g4,1)}	{(g1,1)}	{(g5,1)}	{(g2,1)}	{(g5,1)}
X2	{(g1,1)}	{(g5,1)}	{(g3,1)}	{(g2,1)}	{(g5,1)}	{(g5,1)}
X3	{(g2,1)}	{(g4,1)}	{(g3,1)}	{(g5,1)}	{(g1,1)}	{(g5,1)}
X4	{(g4,0.3),(g5,0.7)}	{(g3,1)}	{(g4,1)}	{(g4,1)}	{(g1,1)}	{(g1,1)}
X5	{(g5,1)}	{(g3,1)}	{(g4,1)}	{(g4,1)}	{(g2,1)}	{(g2,1)}
X6	{(g3,1)}	{(g3,1)}	{(g3,1)}	{(g2,1)}	{(g1,1)}	{(g4,1)}
X7	{(g4,0.2),(g5,0.8)}	{(g2,1)}	{(g3,1)}	{(g5,1)}	{(g2,1)}	{(g4,1)}
X8	{(g3,1)}	{(g3,1)}	{(g5,1)}	{(g5,1)}	{(g3,1)}	{(g2,1)}
X9	{(g4,1)}	{(g1,1)}	{(g3,1)}	{(g5,1)}	{(g3,1)}	{(g1,1)}
X10	{(g2,1)}	{(g5,1)}	{(g5,1)}	{(g5,1)}	{(g4,1)}	{(g4,1)}

2) Evaluation of commodity advertisements based on weighted evidence fusion. Based on the transformed attribute evaluation value matrix, the focal elements under different attributes are determined by DS evidence theory, and the BPA of focal elements under different attributes is calculated. The basic probability assignment values of all the focal elements under the six decision attribute indicators are synthesized, and in order to obtain data with higher support, the data with lower probability after each fusion are excluded, and the basic probability assignment values with higher probability after each fusion are retained. Following this, Bel and Pl are calculated for each commodity advertisement and the corresponding utility preference intervals are determined. Then:

The utility preference intervals for alternative goods advertised X1 are [0,0.0458], and those for X2~X10 are [0.0373,0.0891], [0,0.0312], [0,0261,0.0645], [0,0292,0.0554], [0,0181,0.0642], [0,0272, 0.0593], [0,0.0254], [0,0.0422], [0,0.0536].

The utility values of each alternative commodity advertisement are then compared according to the weighted evidence fusion and judgment rule, e.g., the utility preference intervals of commodity advertisements X1 and X2 are [0,0.0458], [0.0373,0.0891], respectively:

$$p(X1 > X2) = \frac{\max[0, 0.0458 - 0.0373] - \max[0, 0 - 0.0891]}{[0.0458 - 0] + [0.0891 - 0.0373]} = 0.087 \tag{20}$$

Since 0.087<0.5, the utility value of alternative commodity advertisement X1 is much smaller than X2, and by the same reason, the utility value of the 10 alternative commodity advertisements can be ranked as X2>X6>X4>X7>X5>X9>X10>X1>X3> X8. This indicates that among these 10 alternative commodity advertisements, the utility value of commodity advertisement X2 is the largest, and the utility value of X8 is the smallest. The lower ranked ones need to be optimized in six attribute directions based on the higher ranked ones. Therefore, the use of fuzzy evidence theory can realize the precise evaluation of the utility value of social media advertisements and derive the specific path of optimization and improvement of social media advertisements, which can provide help to enhance the marketing revenue of enterprise social media advertisements.

3. Impact of social media advertising optimization on purchasing behaviour

Consumer purchasing behavior prediction can grasp the tendency of consumers' future shopping decisions through the analysis of consumers' online historical behavioral data, which helps enterprises to better locate online value consumer groups and optimize marketing strategies. It is also an important means to improve the decision-making efficiency of e-commerce enterprises and enhance the shopping experience of users, and has been attracting much attention from both the academic and business communities. However, with the continuous development of e-commerce, the online shopping situation is more and more complex, the consumer shopping decision-making psychology is susceptible to the influence of all kinds of factors and changes, and the consumer decision-making psychology is the key to determine the purchase behavior. Therefore, it is especially important to grasp the influence law of consumer purchase behavior to analyze consumer purchase behavior.

The research samples in this chapter come from the data of a certain treasure collected in section 2.3.1, which mainly contains 25,428 social media product advertisements and 5,849 sellers.

3.1. The OLS-LR model and the VAR model

3.1.1. The OLS-LR model. Regression analysis is the study of modeling the relationship between independent and dependent variables. Regression analysis can reveal the degree of influence of the independent variable on the dependent variable, and the resulting model can be used to make the next step in the prediction of the dependent variable [23]. In the application of regression analysis, what is important is the estimation of parameters in the model as well as the test of significance. Firstly, the independent variable X and dependent variable Y are given, where $X=(X_1,X_2,\cdots,X_k), X^{'}=(1,X_1,X_2,\cdots,X_k)$, k are the number of independent variables. β is the parameter to be estimated for the independent variable, where $\beta=(\beta_0,\beta_1,\beta_2,\cdots,\beta_k)^T$, k is the number of independent variables. ε is the random error term.

Then the linear regression model can be expressed as:

$$Y=\beta X^{'}+\varepsilon=\beta_0+\beta_1X_1+\beta_2X_2+\cdots+\beta_kX_k+\varepsilon \tag{21}$$

After building the regression model, it is necessary to solve for parameter β of the model to obtain an estimate of β, $\hat{\beta}$, which is solved by the method of least squares (OLS).

The idea of least squares is to minimize the sum of squares of the residuals to solve for parameter β. From the Gauss-Markov theorem, the assumptions of zero mean, homoskedasticity, and zero covariance of the errors need to be satisfied for the linear regression model to have the best linear unbiased estimate (BLUE).

To minimize the sum of squares of the residuals, it needs to be solved:

$$\min\sum_{i=1}^{n}(y_i-x_i^{'}\beta)^2 \tag{22}$$

where n is the number of sample values. Solving for the minimum residual sum of squares yields the parameter estimates to be estimated $\hat{\beta}$ as:

$$\hat{\beta}=\arg\min_{\beta}\sum_{i=1}^{n}(y_i-x_i^{'}\beta)^2 \tag{23}$$

Regression methods study the relationship between the independent and dependent variables, emphasizing the change in the conditional mean. Parameters in a regression model are generally estimated by least squares OLS, and modeling through regression analysis allows the conditional mean of the dependent variable to be estimated from the independent variable.

3.1.2. VAR model. The VAR model considers all variables as endogenous and regresses the lagged values of all variables with a certain lag length (excluding current values), thus realizing the transition from univariate autoregressive models to multivariate autoregressive models. The purpose of the VAR model is to describe the “data generation process”, so the model is built from the data, without the need for economic theory as a basis, is a kind of unstructured model [24]. VAR model expression is as follows:

$$x_i=A_0+A_1x_{i-1}+A_2x_{i-2}+\cdots+A_px_{i-p}+e_i \tag{24}$$

Among them:

$$x_t = \begin{pmatrix} x_{1t} \\ x_{2t} \\ \vdots \\ x_{dt} \end{pmatrix}, e_t = \begin{pmatrix} e_{1t} \\ e_{2t} \\ \vdots \\ e_{dt} \end{pmatrix}, A_0 = \begin{pmatrix} a_{10} \\ a_{20} \\ \vdots \\ a_{d0} \end{pmatrix} \tag{25}$$

$$A_i = \begin{bmatrix} a_{11}(i) & a_{12}(i) & \cdots & a_{1d}(i) \\ a_{21}(i) & a_{22}(i) & \cdots & a_{2d}(i) \\ \vdots & \vdots & \vdots & \vdots \\ a_{d1}(i) & a_{d2}(i) & \cdots & a_{dd}(i) \end{bmatrix} (i = 1, 2 \cdots p) \tag{26}$$

x_i is a d -dimensional column vector of endogenous variables, $A_f(i = 1, 2 \cdots p)$ is a $d \times d$ -dimensional coefficient matrix, and e_i is a d -dimensional column vector of perturbations. The components are independently and identically distributed. The covariance matrix of residuals e_i is:

$$\sum_{e_i} = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \cdots & \sigma_{1d} \\ \sigma_{21} & \sigma_2^2 & \cdots & \sigma_{2d} \\ \vdots & \vdots & \vdots & \vdots \\ \sigma_{d1} & \sigma_{d2} & \cdots & \sigma_d^2 \end{bmatrix} = E\left(\begin{bmatrix} e_{1t} \\ e_{2t} \\ \vdots \\ e_{dt} \end{bmatrix} \begin{bmatrix} e_{1t} & e_{2t} & \cdots & e_{dt} \end{bmatrix} \right) \tag{27}$$

where $\sigma_{ij} = \sigma_j (i, j = 1, 2, \cdots n)$, $\sum_{e}$ are symmetric arrays.

When performing VAR modeling, the lag order of the variables needs to be determined, as well as several variables included in the VAR system. The first step is the selection of the lag order. There are many methods for lag order selection, the most commonly used is to utilize the information criterion AIC and BIC. Based on the residuals of the VAR model $\hat{e}_i$ the covariance matrix $\hat{\Sigma}_i$ can be estimated, and remembering that the sample capacity is T, the AIC and BIC are calculated as:

$$AIC(p) = \ln |\hat{\sum}_{e_i}| + d(dp+1)\frac{2}{T} \tag{28}$$

$$BIC(p) = \ln |\hat{\sum}_{e_i}| + d(dp+1)\frac{\ln T}{T} \tag{29}$$

The second is the selection of the number of variables in the VAR model, the more variables the VAR model contains, the more coefficients need to be estimated. If there are too many variables, the estimation error will increase and the prediction accuracy will be reduced. And if the model is too small, there may be omitted variable bias.

3.2. Factors influencing purchasing behavior

3.2.1. Research modeling:

1) Research hypothesis. Social media advertising is the use of social media APP for product advertising and promotion as a way to attract the attention of consumers to stimulate their purchasing behavior. Social media advertising can enhance consumers' understanding of products and increase their willingness to purchase them. When consumers form product considerations by eliminating alternatives, they place more emphasis on their specific attributes. When consumers are aware of product attributes from social media ads, they are more likely to purchase those products. Prior research has shown that social media advertisements aim to influence consumers' purchasing behavior by encouraging them to buy products with labels and making them aware of the positive effects of their purchases on them. Therefore, the more receptive consumers are to social media

advertisements, the higher their understanding of the product is likely to be and the higher their willingness to purchase the product. Therefore, we can hypothesize:

H1: Social media advertisements will have a significant positive influence on consumer purchasing behavior.

2) Model Construction. Based on the OLS-LR model proposed in the previous section, the total transaction volume (GMV) of a certain treasure is chosen to quantify consumer purchase behavior and used as the dependent variable. The independent variable is the social media advertising utility (SMA), which can be quantified according to the fuzzy evidence theory proposed in the previous section. In addition, in order to accurately analyze the impact of social media ads on consumers' purchasing behavior, this paper also chooses consumer device type (TYPE), buyer credit (BC), consumer age (AGE), consumer gender (SEX), seller credit (SC), store dynamic rating (SPR), and seller platform (SP) as control variables. As a result, the fixed effects model is obtained as follows:

$$GMV = \beta_0 + \beta_1 SMA + \beta_2 \sum Control + \varepsilon \tag{30}$$

where β_0 is the constant term, $\beta_1 \sim \beta_2$ is the regression coefficient for each variable, $Control$ is each control variable, and ε is the random perturbation term.

3.2.2. Correlation analysis. Before carrying out the regression analysis, the data need to be analyzed for correlation and multicollinearity to ensure that there is no covariance between the variables in the model to affect the regression results. Table 2 shows the matrix of correlation coefficients with the square root of the average variance value, where the values on the diagonal are the square root of the average extracted variance value (AVE). The results show that the correlation coefficients between each variable and the other variables are less than 0.5 and all are less than the square root of their average variance extracted values, thus the discriminant validity of all variables exceeds the accepted level.

Table 2. Correlation matrix and square root of AVE

-	SMA	TYPE	BC	AGE	SEX	SC	SPR	SP
SMA	**0.798**							
TYPE	0.476	**0.824**						
BC	0.483	0.443	**0.806**					
AGE	0.492	0.491	0.428	**0.873**				
SEX	0.457	0.405	0.437	0.479	**0.811**			
SC	0.432	0.478	0.465	0.416	0.418	**0.884**		
SPR	0.469	0.446	0.406	0.472	0.424	0.478	**0.874**	
SP	0.441	0.482	0.434	0.461	0.485	0.435	0.452	**0.898**

Then, the reliability and validity of the variables were tested in this paper, and the results are shown in Table 3. The results show that the factor loadings of social media advertising utility value, consumer device type, buyer's credit, consumer age, consumer gender, seller's credit, store dynamic score and seller's platform are all greater than 0.8, with the minimum value of 0.819. The variance inflation factor (VIF) is less than 3, with the maximum value of only 1.683, which indicates that there is no multicollinearity between the variables, and that it does not have an Impact. The internal consistency reliability (Cronbach's alpha) is more than 0.75, the combination reliability (CR) is more than 0.8, and the AVE is more than 0.6. Therefore, the reliability and validity of the variables in this paper are in the acceptable range, and the regression analysis using the variable data can obtain more accurate results, which can deeply analyze the extent of the influence of the social media advertisements on the consumer's purchasing behavior. In this paper, the reliability and validity of the variables are all in the acceptable range.

Table 3. Reliability and validity of variables

Variable	Factor load	VIF	Cronbach's Alpha	CR	AVE
SMA	0.823	1.362	0.768	0.842	0.637
TYPE	0.867	1.406	0.759	0.867	0.679
BC	0.819	1.417	0.832	0.851	0.650
AGE	0.878	1.683	0.906	0.838	0.762
SEX	0.884	1.469	0.897	0.813	0.658
SC	0.846	1.358	0.795	0.825	0.782
SPR	0.832	1.425	0.833	0.837	0.764
SP	0.851	1.541	0.854	0.896	0.806

3.2.3. Analysis of regression results. OLS, as a classical regression analysis method, is suitable for estimating the positional parameters in linear regression models, and based on the fixed effect model established in the previous section, regression analysis of consumer purchasing behavior is carried out using OLS. Table 4 shows the regression results of consumer purchasing behavior, in which models (1) to (3) are the changes of model parameters without adding control variables and after gradually adding control variables, respectively, and ***,**,* in the table denote the significance levels of 1%, 5%, and 10%, respectively, the same as below, and the robustness errors are shown in parentheses.

In model (1), social media advertising (SMA) has a positive effect on consumer purchasing behavior, with a regression coefficient of 0.438, which possesses a positive and significant correlation with consumer purchasing behavior at the 1% level without considering control variables. Social media advertisements utilize users' relationship networks to facilitate the dissemination of information and increase consumer interaction in the purchasing process. Social media advertising works by embedding consumers' social networks into advertisements, thus utilizing the power of social influence to promote consumers. Social media advertisements are placed based on the interests, needs and preferences of users, and therefore according to targeting and personalization. By analyzing large amounts of user data, social media platforms can provide companies with more precise advertising strategies that can be designed for different consumer groups and marketing objectives.

In model (2)~(4), with the increase of control variables, the influence coefficient of social media advertising on consumer purchasing behavior is gradually decreasing, from 0.438 to 0.179, but it still has a significant positive promotion effect with consumer purchasing behavior at the 1% level. Therefore, the optimization of social media advertising can help to improve consumer purchasing behavior and better obtain economic benefits for enterprises.

In addition, social media advertising has a strong social influence, and people are often influenced by the people around them when making decisions. In social media advertising, this social influence can be given full play to, consumers will see friends or social circle others risk or comment on a commodity and service, this information will have an important impact on the consumer's purchasing influence and judgment, and then stimulate the consumer's purchasing behavior. In conclusion, social media advertising can use the power of social networks to provide consumers with personalized promotions and combine them with social influence to stimulate consumers' purchasing behavior. Thus, H1 is validated.

Table 4. The return of consumer purchases

Variable	Model (1)	Model (2)	Model (3)	Model (4)
SMA	0.438***(0.015)	0.291***(0.013)	0.224***(0.009)	0.179***(0.005)
TYPE	-	0.058***(0.007)	0.056***(0.006)	0.054***(0.004)

BC	-	0.006**(0.002)	0.005**(0.002)	0.005**(0.002)
AGE	-	-	0.003***(0.000)	0.003***(0.000)
SEX	-	-	-0.045***(0.004)	-0.042***(0.005)
SC	-	-	-	-0.047***(0.002)
SPR	-	-	-	3.543***(0.023)
SP	-	-	-	0.516***(0.006)
(Con_)	18.416***(0.085)	18.306***(0.079)	18.237***(0.075)	18.155***(0.071)
R^2	0.438	0.536		0.647
Adj.R^2	0.427	0.519		0.632

3.2.4. Robustness Tests. This study uses the data interception method to ask the hardiness test, based on the calculation of the utility value of social media advertisements, excluding the data of the top 5% and bottom 5% of the rankings, and carrying out the linear regression analysis with the intercepted samples. Table 5 shows the results of the robustness test.

From the results of the robustness test, the value of social media advertising utility (SMA) shows a significant positive correlation with consumer purchasing behavior at the 1% level, with a regression coefficient of 0.185, which is higher than the regression coefficient of the original model. Regarding each control variable, the regression coefficients showed some increase and the significance level was consistent with the original model. The results of the robustness test are consistent with the results of the benchmark regression, and this empirical evidence passes the robustness test. It also shows that social media advertising optimization can enhance consumers' purchasing behavior, and enterprises need to fully understand consumers' purchasing preferences and so on when carrying out marketing, and design social media advertisements that are more in line with consumers' behaviors in order to better enhance consumers' purchasing intentions.

Table 5. Robustness test results

Variable	Primary model		Robustness test	
	Coefficient	P value	Coefficient	P value
SMA	0.179***	0.005	0.185***	0.008
TYPE	0.054***	0.004	0.072***	0.009
BC	0.005**	0.002	0.012**	0.005
AGE	0.003***	0.000	0.009***	0.002
SEX	-0.042***	0.005	-0.028***	0.009
SC	-0.047***	0.002	-0.031***	0.012
SPR	3.543***	0.023	3.689***	0.035
SP	0.516***	0.006	0.861***	0.017
(Con_)	18.155***	0.071	20.667***	0.086
R^2	0.647	-	0.685	-

3.3. Dynamics of Purchasing Behavior

3.3.1. Research modeling. Aiming at the dynamic change of consumers' purchasing behavior, this paper starts from AIDA theory, for consumers' different social media advertising channels, it is divided into enterprise-initiated channels (FICs) and customer-initiated channels (CICs), and in this way, analyzes the influence of dynamic channels of social media advertisement on consumers' purchasing behavior. Among them, FICs mainly include four categories of SMS, email, WeChat, and referral, and CICs include five categories of brand search, direct input, and price comparison. The specific content is shown in Table 6.

Table 6. Model variable selection

-	-	Variable	Describe
Social media Advertising	CICs	BrandSEA	Daily brand paid search advertising clicks
		GenericSEA	Every day, the number of ads for advertising
		BrandSEO	Daily brand natural search clicks
		GenericSEO	Daily natural search clicks
		Direct	Direct input per day
	FICs	SMS	SMS ads per day
		EMA	Email ads per day
		WECHAT	Daily WeChat public number push clicks
		REFER	Click the number of links per day
Consumer access	HomePage		The number of sessions visited every day
	Detail		The number of sessions that are accessed per day on the product details page
	Cart		The number of sessions that add to the shopping cart every day
Purchase behavior	PUR		Customer purchase times per day

After specifying the research variables, this paper constructs the following advertising effect model based on the VAR model:

$$\left\{\begin{matrix} Advertising_t \\ Homepage_t \\ Detail_t \\ Cart_t \\ PUR_t \end{matrix}\right\} = A + B_t \left\{\begin{matrix} Advertising_t \\ Homepage_t \\ Detail_t \\ Cart_t \\ PUR_t \end{matrix}\right\} + \sum_{k=1}^{p} \phi_k \left\{\begin{matrix} Advertising_{t-k} \\ Homepage_{t-k} \\ Detail_{t-k} \\ Cart_{t-k} \\ PUR_{t-k} \end{matrix}\right\} + \varepsilon_t \tag{31}$$

Where B_t is the parameter matrix of short-term effect, which represents the current period impact and immediate effect of one unit change of a variable (e.g., clicks on a social media advertising channel) on other variables (e.g., visits to the home page, visits to the detail page, the number of add-to-cart, or the number of purchases), which is a reflection of the immediate effect of social media advertising. ϕ_k represents the impact of one unit shock of a variable on other variables in the subsequent period k, which represents the long-term effect. These sets of coefficients are known as impulse response functions. Impulse response means how a shock to a variable will dynamically affect that variable as well as other variables.

3.3.2. Determining the optimal lag order. Before constructing the VAR model, the collected data must be tested for smoothness, because the establishment of vector autoregressive model requires the use of smooth data, if the data used to establish the model is not smooth, it will cause the established model to be unstable, which will result in the phenomenon of pseudo-regression, and therefore the obtained analytical results will not be true. Therefore, in this paper, in order to avoid this phenomenon, each variable is first logarithmized before establishing the VAR model, and then the unit root test is used to verify the smoothness of the data. The test results show that the variables under the 1st order logarithm are non-stationary data, so the variables are made stationary at the 1% level by performing the 1st order differencing.

The lag order of the VAR model can reflect the complete dynamic characteristics of the whole model, but the choice of the lag order should be neither too large nor too small, if the lag order is too large, although the established VAR model can capture more information, but with the increase of the lag order will reduce the degrees of freedom of the system of equations, which will reduce the accuracy of the estimation of the established model. Therefore, the optimal lag order should be a balance between capturing more information and decreasing the degrees of freedom. In this paper, the optimal lag order is determined by employing a variety of principles, including the likelihood ratio test (LR), the final prediction error criterion (FPE), the Akaike Information Criterion (AIC), the Schwartz Criterion (SC), and the Hannon-Queen Criterion (HQ), etc., and selecting the one that satisfies the most to determine the optimal lag order. Table 7 shows the optimal lag order selection criteria run through EViews software. In the table, the one bolded with * is the optimal lag order. From the table, it can be seen that by weighing the five criteria of LR, FPE, AIC, SC, and HQ, the order with the most * signs is taken as the optimal lag order of the model, so the optimal lag order of the VAR model designed in this paper is 4 orders.

Table 7. Optimal lag order selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	391.04	-	5.636e-15	-21.12	-22.35	-20.12
1	390.76	3.486	3.621e-15	-22.28	-22.79	-21.17
2	367.03	6.667	7.516e-15	-21.81	-22.52	-23.23
3	362.49	7.071	4.419e-15	-20.75	-21.36	-20.71
4	407.88	**127.914***	**8.173e-16***	**-24.36***	**-24.15***	**-24.63***
5	395.65	4.096	6.485e-15	-20.89	-22.95	-20.47
6	408.13	3.939	4.082e-15	-20.27	-21.89	-20.52
7	414.31	7.094	5.794e-15	-21.86	-21.59	-20.73
8	353.66	3.054	5.681e-15	-20.33	-21.34	-21.91
9	385.52	4.015	4.072e-15	-20.41	-21.48	-20.45
10	391.04	3.912	3.749e-15	-21.90	-22.36	-20.18

Before performing the impulse response analysis, it is important that we perform a robustness test on the model developed. This is because a stable VAR model allows whichever variable in the model is affected by an external shock to reduce the effect of that external shock over time and in the end can bring the system to a new equilibrium state. If the VAR model developed is non-stationary or poorly stabilized, after any of the variables in the model is affected by an external shock, the effect of that shock on a particular variable becomes more and more significant and often ends up invalidating the model. This paper utilizes the unit circle test to test the stability of the vector autoregressive model developed. By observing the results of the unit circle test, it is found that all the characteristic roots of the established VAR model are less than 1 and fall within the unit circle, so the VAR model designed in this paper is stable.

3.3.3. Impulse Response Function Analysis. After identifying the optimal lag order, a VAR model can be constructed and estimated for each of the nine channels.The B_t-parameter matrix in the VAR model reflects the current impact of the variables. In this paper, we use the B_t-parameter matrix to measure the short-term effect of each social media advertisement on consumers' final purchase by using the current profit of the enterprise to measure the short-term effect. Table 8 shows the key estimation results of the VAR model for the nine social media advertising channels.

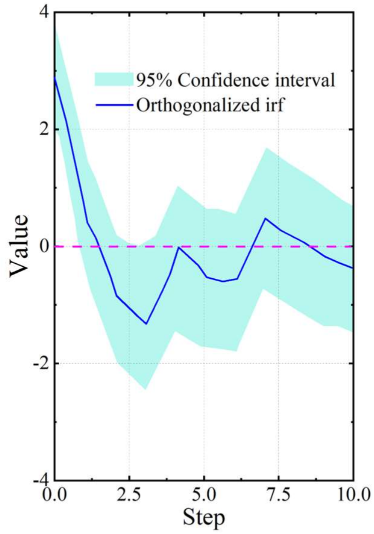
From the results in the table, it can be seen that the short-term effect of CICs branded social media advertisements is the largest and highly significant, the short-term effect of CICs generic social media advertisements is the second largest and highly significant, the short-term effect of FICs social network advertisements is the smallest, and the short-term effect of email advertisements is weakly significant. Overall, CICs social media advertisements are more effective than FICs social media advertisements in promoting consumer purchasing behavior over a short period of time.

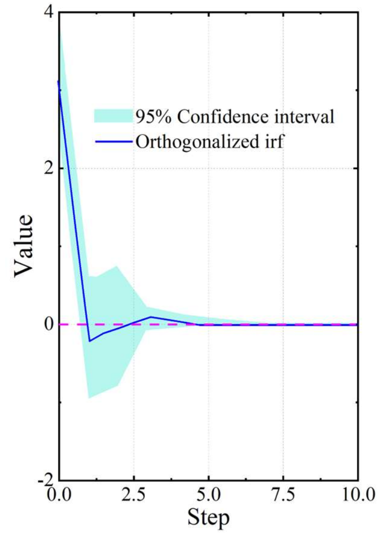
Table 8. Short-term effects of different types of social media advertising

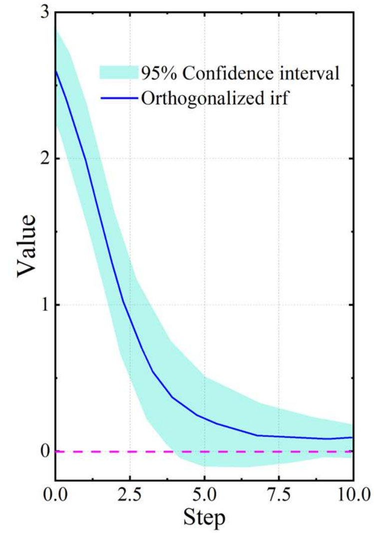
Classify	Variable	Short term effect	Std	P value	Confidence interval
CIC Brand	BrandSEA	0.276***	0.049	0.002	[0.183,0.356]
	BrandSEO	0.251***	0.045	0.001	[0.157,0.334]
CIC Generic	Direct	0.243***	0.073	0.000	[0.172,0.315]
	GenericSEA	0.185**	0.082	0.015	[0.006,0.367]
	GenericSEO	0.176**	0.064	0.027	[0.035,0.324]
FIC	SMS	0.105**	0.079	0.033	[0.003,0.215]
	EMA	0.076*	0.051	0.082	[-0.001,0.171]
	WECHAT	0.106*	0.062	0.074	[-0.015,0.232]
	REFER	0.145**	0.073	0.041	[0.015,0.279]

Since the VAR model contains many parameters whose significance is difficult to interpret, the analysis is often based on generating orthogonalized impulse response plots of the model to capture the dynamic effect of each variable on other variables in that system. In this paper, we focus on the dynamic change process of consumer purchase behavior caused by nine social media advertisements as shock variables, as shown in Figure 2, and the impulse response results of the nine variables are shown in Figures 2(a)~(i), respectively.

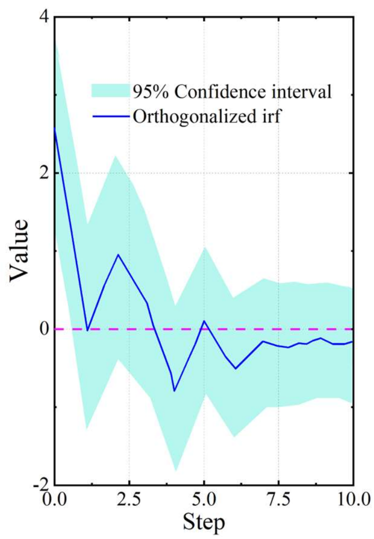
The blue dash line in the figure shows the change in the response of one variable induced by a one-unit standard deviation shock to the other variable, the light blue area is the confidence interval between positive and negative standard deviations, and the horizontal line marks the null axis of y=0 (pink line), which indicates that the effect is not significant if the confidence interval contains the null axis. First, looking at the shock response plots for branded online ads in the CICs, Figure (a) shows that a one standard deviation shock for branded paid search social media ads has a positive impact effect on consumer purchasing behavior within one day, which then diminishes, and the impact effect is not significant after one day. Similarly, Figure (b) shows that the one standard deviation shock of branded natural search social media ads has a positive impact on consumer purchase behavior and this effect occurs on the same day and then gradually weakens and converges. In addition, direct visits as one of the CICs social media advertisements also have a positive shock effect on consumer purchase behavior in the short run, and this positive shock effect converges to zero after 7 days (Figure (c)). Second, from CICs generic social media ads, the impact of generic paid search social media ads and generic search marketing social media ads on consumer purchase behavior occurs around 2.5 days, and then the effect tends to level off. Finally, in terms of FICs social media ads, the impact of SMS ads on consumer purchase behavior is long-lasting, with the effect fading to zero by day 10. In contrast, a one-unit standard deviation shock to email ads first has a positive effect on consumer purchasing behavior for 5 days and then tapers off. And then from the 6th day onwards there is a lagged effect which lasts until the 10th day, when the effect disappears. The one unit standard deviation shock of the micro-channel promotion ads fades quickly within the first day and then produces a weaker lagged effect around day 6 and lasts until day 10. The referral ads have a shorter impact time relative to the other FICs ads. From the above analysis, it can be seen that in the short term CICs social media advertisements have a positive effect on consumer purchase behavior. And in the long run, FICs social media ads have a more sustained effect on consumer buying behavior.

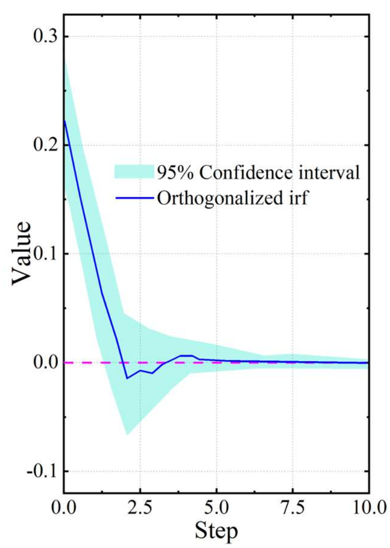


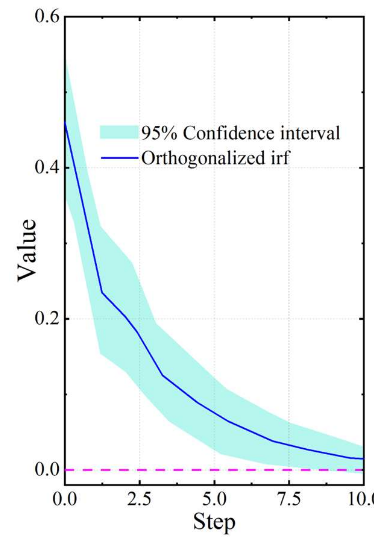




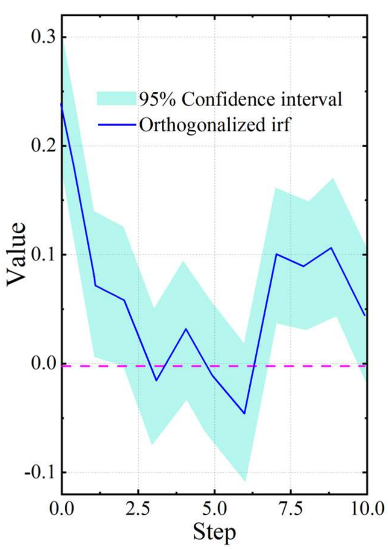
(a) BrandSEA (b) BrandSEO (c) Direct

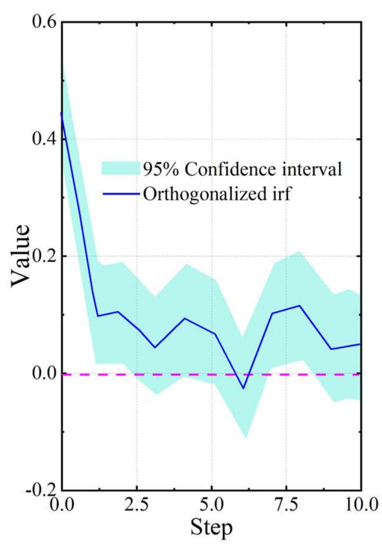


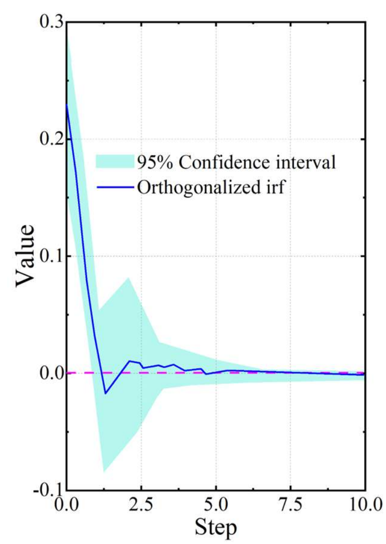




(d) GenericSEA (e) GenericSEO (f) SMS







(g) EMA (h) WECHAT (i) REFER

Fig. 2. Pulse response of different social network advertising channels

4. Conclusion

The article proposes an optimization and evaluation model of social media advertisements that combines fuzzy set theory and DS evidence theory, and analyzes the influencing factors and dynamic changes of social media advertisements on consumers' purchasing behaviors through OLS-LR model and VAR model. Based on the fuzzy evidence theory, the calculation of the utility value of commodity advertisements in social media can be realized, and based on the calculation results, the ranking can be carried out to realize the optimization of social media advertisements, and then stimulate the purchase intention of consumers. Considering the control variables, the regression coefficient of the utility value of social media advertisements on consumer purchasing behavior is 0.179, and it shows positive significance at the 1% level. A 4th-order VAR model is used to explore the effects of different types of social media advertising channels on consumer purchasing behavior, in which CICs social media advertisements are more focused on short-term effects, while FICs social media advertisements tend to have long-term effects.

In conclusion, the exploration of the optimization path of social media advertisements can be realized by combining the fuzzy set theory, and the related factors affecting consumers' purchasing behavior can be identified by combining the regression analysis, which provides a reliable technical support and data mining method for enterprises to optimize their own marketing strategies.

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