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Promote or inhibit? Research on the transition of consumer potential purchase intention

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Abstract
A dramatic shift from offline to online has happened in consumer behavior, leading to enterprises ploughing a large number of digital advertisements to capture consumers' attention online. To evaluate the effectiveness of different online advertising, we explore the dynamic impacts of nine different online channels on the transition of consumers' potential purchase intention and the consumer behavior. We use a continuous-time hidden Markov model (CT-HMM) to capture the transfer path of consumers who are affected by various online channels. Our findings reveal that online advertising has a positive and statistically significant impact on the transition of consumer purchase intention, of which search advertising can significantly increase consumers' propensity to purchase, and its effect on transferring consumers from high to low purchase intention is not very strong in comparison. However, consumers have a very low annoyance threshold to short messaging service (SMS) advertising, and they are easy to get tired of SMS advertising and transfer to low purchase intention. Most firm-initiated advertising is more likely to transfer consumers to a low purchase intention state. Advertisements which can not improve consumer purchase intention very well have fewer stimulating effects on consumers' information collection behavior than other advertisements. Our research contributes to the literature on the effectiveness of online advertising and provide some management insights for enterprises.

Keywords Consumer potential purchase intention · Online advertising · Dynamic model · Continuous-time hidden Markov model

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1 Introduction

Driven by big data, a dramatic shift from offline to online has happened in consumer behavior, making consumers more willing to collect information and purchase through online channels than through traditional offline channels when they are interested in a product. The shift in consumer behavior has led to a subsequent change in the behavior of enterprises. As consumers spend increasing amounts of time on the Internet, enterprises are beginning to pay a growing concern on how to get consumers' attention online. Therefore, a large number of online advertisements has been ploughed on the market. It is reported that the worldwide online advertisement spending will reach \$491.70 billion in 2021 and increase to \$500 billion in 2022 (eMarketer, 2021). With the increasing spending on online advertising and the diversification of online advertising channels, how to effectively capture potential consumers and enhance consumer purchase intention in the clutter of information has become the focus of research.

However, there is growing evidence that online advertising can cause consumer annoyance (Todri et al., 2020). The digitalization has increased consumer control over advertising (Wilbur, 2015). It is easy for consumers to block online ads by fast-forwarding or shutting them down when encountering ads in distaste (Wilbur, 2008). Consumers have distinct tolerance levels for different types of online advertising (Shen and Miguel Villas-Boas, 2018), therefore, the effectiveness of online advertising can be affected by its type. Although enterprises can enhance the coverage of consumers to a certain extent by blindly expanding the diversity of online advertising, they face the risk of low efficiency and high cost. Researchers have studied the effectiveness of online advertising in terms of ad click probability, ad click-through-rate, purchase intention, sales volume, etc (Nottorf, 2014; Summers et al., 2016; Kim et al., 2011). There is relatively little literature exploring the effectiveness of online advertising from the perspective of consumers' potential state before purchase. Nevertheless, it is a dynamic process for consumers from contacting advertising to purchasing products. Consumers generate different behaviors and shift between potential states before making a purchase decision. How to measure the changes in the potential state of consumers before purchase is of great significance for the evaluation of online advertising effect.

In this paper, we use a hidden Markov model to explore the potential state transition of consumers under nine channels in a large e-commerce enterprise. The nine channels mainly include: (1) Direct type-in. Consumers access the website directly by typing the URL of the e-commerce enterprise into the address box of their browser. (2) Brand paid search advertising. The enterprise improves the website ranking under brand keywords by paying fees to search engines. Consumers visit the website by clicking on the paid search advertising link after entering the brand keyword in the search engines. (3) Generic paid search advertising. The enterprise improves the website ranking under generic keywords by paying fees to search engines. Consumers visit the website by clicking on the paid search advertising link after entering the generic keyword in the search engines. (4) Brand organic search advertising. The enterprise optimizes their natural rankings under brand keywords in search engines by investing large amounts of money. Consumers visit the website by clicking on the organic links after entering the brand keyword in the search engines. (5) Generic organic search advertising. The enterprise optimizes their natural rankings under generic keywords in search engines by investing large amounts of money. Consumers visit the website by clicking on the organic links after entering the generic keyword in the search engines. (6) Short messaging service (SMS). The enterprise pushes the advertisement to the target consumers in the form of text and link SMS content, and the consumer visit the enterprise's website by clicking the link. (7) Email. The enterprise pushes the advertisement to the target consumer via email, and the consumer visit the enterprise's website by clicking the link. (8) WeChat. The enterprise pushes the advertisement in the article of WeChat official account, and consumers visit the website through clicking the link. (9) Affiliate programs. The enterprise places the advertising link on the third-party websites, and consumers visit the enterprise's website through clicking the link. When the consumer completes a purchase through the link, the third party will receive a commission fee from the enterprise. In order to achieve the research object, we mainly focus on addressing the following questions: (1) What are the potential state transfer paths of consumers under nine different channels? How does online advertising in different channels affect the potential state transfer of consumers? (2) What are the differences in consumers' behavior under different channels of online advertising? (3) How should enterprises effectively advertise according to the potential state of consumers before purchase?

Our study finds that online advertising is a double-edged sword. Online advertising can not only enhance consumers' purchase intention but also reduce consumers' purchase intention. Effects of online advertising on the transition of consumer purchase intention varies across the online advertising types. For consumer-initiated advertising channels (four types of searching advertising) and affiliate programs, the effect of promoting the transfer of consumers from low purchase intention to high purchase intention is stronger than promoting the transfer of consumers from high purchase intention to low purchase intention. And for SMS, WeChat as well as email advertising, the reducing effect will be stronger than the enhancing effect. It can be seen that advertisements initiated by firms are more likely to cause consumer discontent, however the dissatisfaction will be reduced when consumers contact with the company through a third-party website. Moreover, the consumer behavior under two hidden states reflects that consumers are more likely to enhance their information collection behavior when they raise the propensity to purchase. Online advertising will reduce consumers' information collection behavior, and advertisements which do not perform well in transferring consumers to high purchase intention have fewer stimulating effects on consumers' information collection behavior than other advertisements.

The contributions of our research are as follows. First, we have enriched the literature on the evaluation of online advertising effectiveness through evaluating the effectiveness of online advertising from the perspective of consumers' potential states, which is ignored by most current literature. Capturing the transfer of consumers' potential state can help enterprises better explore potential consumers and avoid causing consumer aversion, and can explain why the effectiveness of online advertising varies across the online advertisement types. Second, we evaluate and compare consumer transfer paths under nine channels, encompassing firm-initiated advertising channels (SMS, WeChat, email, affiliate programs), consumer-initiated advertising channels (searching advertising), and channels directly accessed by consumers (direct type-in), which can better help enterprises identify the role of various types of advertising channels. Third, we analyze the behavior of consumers of various channels under two hidden states, so as to help enterprises further contact consumers.

2 Literature review

The emergence of various social media has increased the interaction channels between enterprises and users, thus greatly enriching the formats of online advertising. The diversification of online advertising formats makes scholars' research on online advertising more detailed. Our study is related to three streams of literature. The first stream is the effectiveness of online advertising. To explore the effectiveness of advertising, Sridhar et al. (2016) divide advertising into three types: national, regional and online, and find that online advertising can increase the enterprise performance but will decrease the effectiveness of other two advertising. Bleier & Eisenbeiss (2015) use the data from two large-scale field experiments and two lab experiments to investigate the effectiveness of ad personalization, and the result shows that personalized online advertising can increase consumer click-through rates, particularly at the early information stage of the purchase decision. Bruce et al. (2017) develop a dynamic zero-inflated (DZI) count model to evaluate the effectiveness of static and animated display advertising by using the data of daily impressions, clicks, targeting, and ad creative content, and they consider the impact of different ad contents on effectiveness. Sahni et al. (2018) find that personalizing the emails can benefit the advertisers. The probability for consumers to open the email will increase and the number of consumers to unsubscribe the email will decrease by adding the consumers' name in the message. Hoban & Bucklin (2015) study the effectiveness of online display advertising at the different stage of the purchase funnel, the results show that online display advertising has a positive impact on consumers in most stages of the purchase funnel, but has little impact on consumers who have previously accessed the website without creating an account. It can be seen that most of the current literature have examined the effects of online advertising on click-through rates, enterprise performance, sales, and so on. While the analysis of these indicators can reflect the effectiveness of online advertising in terms of economic effects, it ignores the impact of online advertising on the dynamic changes of potential consumers. The consumer state transfer path before purchase behavior can reflect the consumer attitude toward online advertising, therefore, we focus more on the potential state between consumers visiting the website through advertising and making purchase decisions, which can help enterprises to explore potential consumers and retain original consumers.

The second stream is the comparison of different online advertising channels. The various types of online advertising play different roles in influencing consumers' decisions, which needs the researchers to conduct in-depth studies on online advertising. Bayer et al. (2020) analyze the impact of paid search advertising and display advertising on enterprise performance and enterprise value by using the data of 1651 enterprises in seven years. The results show that different types of advertising have different economic benefits, and both advertising will have a positive impact on enterprise performance. Danaher & Dagger (2013) develop a method to assess the relative effectiveness of multiple advertising media, and find that most of the advertisements will significantly influence the purchase. And they construct an advertising response model to determine the optimal budget allocation for each advertising channel. Li & Kannan (2014) explore the incremental value of display advertising, paid search advertising, referral advertising and e-mail, and analyze the consumers' consideration of online channels, visits and subsequent purchases. Dinner et al. (2014) analyze how the expenditures, impressions and click-through rate of online display advertising, search advertising and traditional media translate into sales. Xu et al. (2014) develop a Bayesian hierarchical model to evaluate the conversion effects of various types of online advertising, and find that online display advertising has low direct effect on purchase conversions relative to other advertising, but can stimulate subsequent visits through other online advertising. Through literature review we find that different advertising channels can have various effects on enterprise performance, click-through rates and purchase conversion rates. To enrich the literature in the effects of online advertising on consumers' hidden states, we analyze the state transfer path in nine major access channels. In addition, the current literature in this area rarely compares advertising channels with the ad-avoidance channel. However, a consideration of ad-avoidance channel helps us to intuitively analyze the effectiveness of online advertising. Therefore, we also construct a hidden Markov model of the direct type-in channel.

The third stream of literature related to our work is the application of hidden Markov model (HMM) in marketing. Hidden Markov model is commonly used in fields such as speech recognition, biological sequence data analysis, and can also be used to analyze longitudinal data at the individual level (Juang and Rabiner, 1991; Durbin et al., 1998; Singh et al., 2014). At present, HMM has been widely applied in the field of marketing. Ascarza et al. (2018) capture different types of consumer churn by constructing a hidden Markov model and analyze the impact of communication quality of different enterprises on consumer behavior and the transfer of consumers between different potential states. The study shows that the overt churners tend to engage in more interactions before terminating their relationship with the enterprise, while silent churners rarely engage in interactions. Netzer et al. (2008) construct and estimate a hidden Markov model to study the transfer between consumers' potential relationship states and the effect of consumer-enterprise contact on subsequent purchase behavior. Park et al. (2018) explore the impact of price discounts as well as non-price free sample coupons on consumer purchase behavior by constructing a hidden Markov model to capture the dynamic changes in consumer purchase behavior, and analyze the long-term and short-term effects of mobile promotions. Todri et al. (2020) analyze the impact of display advertising on consumers' purchase decision by constructing HMM, and discuss the relationship between consumers annoyance and advertising effectiveness. The research shows that display advertising can promote consumers to transfer between purchase funnel states, but excessive advertising exposure will cause consumers annoyance. It can be seen that using hidden Markov model can well explore the hidden relationship between consumers and enterprises, as well as the change of consumers' potential attitude. In our study, the unobserved consumer potential states in hidden Markov model are combined with the observed consumer purchase behavior and information collection behavior. However, in most hidden Markov models, the observations occur at fixed time intervals, which means that the length of the time period is the same for all individuals. When the observations occur at irregular time occasion, the computation complexity increases, and at this time we may use a continuous-time hidden Markov model (CT-HMM) to solve the problem (Sahoo et al., 2012). For example, Zhou et al. (2021) construct a multidimensional, continuous-time hidden Markov model to capture individuals' self-regulatory dimensions so as to evaluate the effectiveness of social media on individual weight management. Since the longitudinal access data at the individual level is dynamic access data in this paper, consumers' observations have different length of the time period. Therefore, a continuous-time hidden Markov model is developed to reflect the dynamic change process.

3 Model development

3.1 Data overview

The data used in this study comes from a large e-commerce enterprise in China. The enterprise mainly provides consumers with more than one hundred brands of insurance products, including global travel insurance, cargo insurance, medical and health insurance, car insurance and so on. Before the outbreak of COVID-19, low price and high purchase frequency made travel insurance an important component of the enterprise revenue. However, the main component of the enterprise revenue has shifted to medical and health as well as other insurance products after the outbreak of COVID-19. In order to avoid the impact of the change in the revenue structure on our study results, the observation window is selected from January 1, 2018 to January 31, 2020. To explore the hidden state and state transfer of consumers under different channels, the following data processing work is carried out in this paper. First, by identifying the access source field in the user-behavior log table, we mark the different access channels of consumers. We eliminate access channels with few data, such as Micro-blog and TikTok, and finally choose nine main access channels, including direct type-in, brand paid search advertising, generic paid search advertising, brand organic search advertising, generic organic search advertising, SMS, email, WeChat and affiliate programs. Second, we identify the complete access behavior of the same user. As the user can access the website through mobile terminal or PC terminal, the user identity should be matched to seek out the integrated access path. We match the user cookie with user matching table to discern the user ID, and delete unidentifiable user data. Subsequently, the access records and transaction records are recognized according to the matched user ID. Third, we divide the access data at the consumer-day level and eliminate invalid and abnormal data such as crawlers and non-manual clicks, and we obtain 429,520 pieces of data. Then we retain only the data of consumers who visited the website more than seven times during the observation window to improve the validity of the study. Finally, we obtain 123,359 pieces of data. Table 1 provides the descriptive statistics of relevant variables.

3.2 Conceptual model

There are two major ways for consumers to access the website of the enterprise, one is the ad-avoidance channel and the other is the advertising channel. The ad-avoidance channel, direct type-in, refers to consumers accessing the website directly by typing the URL of the e-commerce enterprise into the address box of their browser. And the advertising channels, four search advertising, SMS, email, WeChat as well as affiliate programs, refer to consumers accessing the website through the advertising links. Consumers' unobserved hidden states,

Table 1 Descriptive statistics of relevant variables

Variable	Mean	Standard deviation
Direct type-in click (0 = No, 1 = Yes)	0.6508	0.4767
Brand paid search advertising click (0 = No, 1 = Yes)	0.1548	0.3617
Generic paid search advertising click (0 = No, 1 = Yes)	0.0638	0.2444
Brand organic search advertising click (0 = No, 1 = Yes)	0.0389	0.1934
Generic organic search advertising click (0 = No, 1 = Yes)	0.1993	0.3995
SMS click (0 = No, 1 = Yes)	0.0347	0.1831
Email click (0 = No, 1 = Yes)	0.0267	0.1613
WeChat click (0 = No, 1 = Yes)	0.0739	0.2616
Affiliate programs click (0 = No, 1 = Yes)	0.0068	0.0820
Online purchase (0 = No, 1 = Yes)	0.2580	0.4375
Web pages viewed	13.1484	16.9807

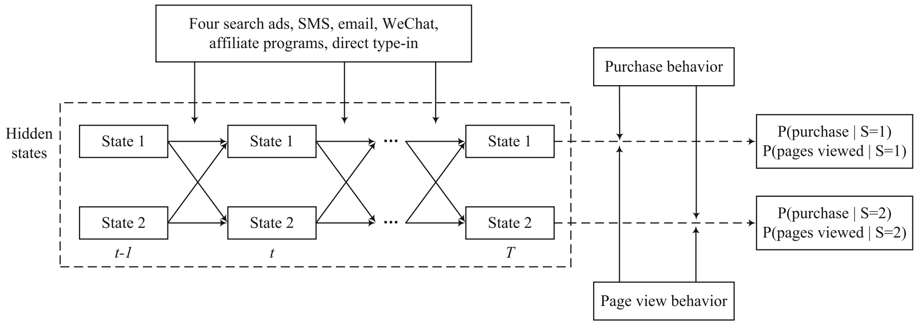

Fig. 1 The dynamic model diagram of consumer purchase

which are reflected by the observed purchase behavior and page view behavior, can transfer with time, and the diversion will be influenced by the channels through which consumers access the website. In order to simplify the model, we only consider two hidden states, that is $State \in \{1 = low\ purchase\ intention,\ 2 = high\ purchase\ intention\}$. In two states, the probability of consumer behavior being observed is different. We assume that consumers with low purchase intention have less purchase possibility and information collection behavior than those with high purchase intention. Figure 1 shows the graphical representation of consumer purchase dynamic model.

3.3 Hidden Markov model

In this paper, we use a hidden Markov model to analyze the consumer purchase intention transfer dynamics under different channels. Let $S(i) = (S_{i1}, S_{i2}, \cdots, S_{iT})$ represent the hidden state of consumer i in time periods $t = 1, 2, \cdots, T$, where $S_{it} = \{1 = low\ purchase\ intension,\ 2 = high\ purchase\ intension\}$. Let $O(i) = (O_{i1}, O_{i2}, \cdots, O_{iT})$ represent the observed outcome sequence of consumer i in time periods $t = 1, 2, \cdots, T$, where $O_{it} = \{Y_{it}, V_{it}\}$. Y_{it} is the purchase behavior of consumer i in time period t, and V_{it} is the number of pages viewed by consumer i in time period t.

The basic HMM is comprised of the initial-state distribution π, the transition probability matrix A, and the emission matrix B, and the parameter set is $\lambda = \{\pi, A, B\}$. The initial-state distribution $\pi(i) = (\pi_{i1}, \pi_{i2}, \cdots, \pi_{iS})$, where $\pi_{iS} = P(S_{i1} = j)$ is the initial probability that consumer i is in state j in time period 1. The transition probability matrix $A(i, t, t+1)$ is defined as the matrix with element $a_{it}(j, k)$, where $a_{it}(j, k) = P(S_{it+1} = k \mid S_{it} = j)$ is the probability that consumer i is in state s in time period j and transfer to state k in time period $t+1$. The emission matrix $B(i, t)$ is defined as the matrix with element $b_{it}(O_t)$, where $b_{it}(O_t) = P(O_{it} = g \mid S_{it} = j)$ is the probability of observing the outcome g conditional on consumer i is in state j at time t. From the Markov assumption we can obtain

$$P(S_t \mid S_1, S_2, \cdots, S_t) = P(S_t \mid S_{t-1}). \tag{1}$$

The observed outcome sequence depends only on the state in time period t and not on the states or observations of the previous time, therefore,

$$P(O_t \mid O_1, \cdots, O_t, S_1, \cdots, S_t) = P(O_t \mid S_t). \tag{2}$$

Given $S(i)$ and λ, the probability of observing $O(i)$ is

$$P(O(i) \mid \lambda, S(i)) = \prod_{t=1}^{T} b_{it}(O_t). \tag{3}$$

And the probability of $S(i)$ conditional on λ is

$$\begin{aligned} P(S(i) \mid \lambda) = P(S_{i1}, S_{i2}, \cdots, S_{iT} \mid \lambda) &= P(S_{iT} \mid S_{i1}, S_{i2}, \\ &\quad \cdots, S_{iT-1}, \lambda) \cdot P(S_{i1}, S_{i2}, \cdots, S_{iT-1} \mid \lambda) \\ &= P(S_{iT} \mid S_{iT-1}) \cdot P(S_{i1}, S_{i2}, \cdots, S_{iT-1} \mid \lambda) \\ &= a_{iT-1,iT} \cdot a_{iT-2,iT-1} \cdots a_{i1,i2} \cdot \pi(i). \end{aligned} \tag{4}$$

Then, the likelihood of observing $O(i)$, which is the probability of $O(i)$ given $S(i)$ and λ, will be denoted by

$$\begin{aligned} L(O(i)) &= P(O(i) \mid \lambda) \\ &= \sum_{\forall S(i)} P(O(i), S(i) \mid \lambda) \\ &= \sum_{\forall S(i)} P(S(i) \mid \lambda) \cdot P(O(i) \mid \lambda, S(i)) \\ &= \sum_{S_1} \sum_{S_2} \cdots \sum_{S_T} \pi(i) \prod_{t=2}^{T} a_{it-1,it} \prod_{t=1}^{T} b_{it}(O_t). \end{aligned} \tag{5}$$

To simplify Equation (5), we express it in matrix form (Zucchini and MacDonald, 2009)

$$L(O(i)) = \pi(i)B(i,1)A(i,1,2)B(i,2)A(i,1,2)\cdots A(i,T-1,T)B(i,T)\mathbf{1}', \tag{6}$$

where $\mathbf{1}$ is a 2×1 vector of ones.

3.3.1 The transition intensity matrix *Q*

The longitudinal data used in this study are a series of behavioral data generated by consumers, which are recorded after intermittent visits to the website at irregular and different time intervals. Since the access dynamic of the consumer is a continuous process, the continuous-time hidden Markov model will be more applicable to our study (Jackson, 2011). In the CT-HMM, we use the transition intensity matrix $Q(i,t)$ with element $q_{it}(j,k)$ to reflect the transfer between hidden states of consumer i in time period t,

$$q_{it}(j,k) = \lim_{\delta t \to 0} \frac{P(S_{it+\delta t} = k \mid S_{it} = j)}{\delta t}. \tag{7}$$

The relationship between the transition probability matrix and the transition intensity matrix can be obtained from Kolmogorov forward (Cox and Miller, 2017):

$$\frac{\partial A(i,t,t+1)}{\partial t} = A(i,t,t+1)Q(i,t), \tag{8}$$

$$A(i,t,t+1) = Exp(tQ(i,t)). \tag{9}$$

We assume that the transition intensity matrix $Q(i,t)$ of consumer i in time period t is affected by the channel through which consumers visit the website, then the transition intensity under the direct type-in (d), brand paid search advertising (bp), generic paid search advertising

(gp), brand organic search advertising (bo), generic organic search advertising (go), SMS (s), email (e), WeChat (w) as well as affiliate programs (ap) is

$$q_{it}^{Z}(j, k, Z_{it}) = q_{it}^{Z(0)} exp((\beta_{jk}^{Z})^{\top} Z_{it}), \tag{10}$$

where $q_{it}^{Z(0)}$ is the baseline transition intensity, and $Z = \{d, bp, gp, bo, go, s, e, w, ap\}$. And we assume that the transition intensity from low purchase intention to high purchase intention equals to the transition intensity from high purchase intention to low purchase intention, that is $q_{12} = q_{21}$.

3.3.2 The emission matrix *B*

We use the purchase behavior and the web page view behavior of the consumer to reflect the unobserved consumer purchase intention, that is $O_{it} = \{Y_{it}, V_{it}\}$. $P(Y_{it} = 1 \mid S_{it} = j)$ denotes the probability of consumer in time period t to purchase under the hidden state j, and we can obtain

$$P(Y_{it} = 1 \mid S_{it} = j) = prob_j = \frac{exp(\gamma_j)}{1 + exp(\gamma_j)}; \; j = \{1, 2\}, \tag{11}$$

we assume that the decreased purchase intention is accompanied by a decrease in the probability of consumers to purchase, hence $prob_1 \leq prob_2$.

$P(V_{it} = n_{it} \mid S_{it} = j)$ denotes the probability of consumer in time period t viewing n_{it} web pages under the hidden state j. To prevent gradient exploding problem, we normalize the web pages viewed by consumers and assume that the variable n_{it} obeys Gaussian distribution with an expectation μ_j and a standard deviation σ_j. We can obtain

$$P(Y_{it} = n_{it} \mid S_{it} = j) = \frac{1}{\sqrt{2\pi\sigma_j^2}} exp(-\frac{(n_{it} - \mu_j)^2}{2\sigma_j^2}); \; j = \{1, 2\}. \tag{12}$$

Since the consumer information collection behavior will increase as the purchase intention increases, the restriction $\mu_1 \leq \mu_2$ is implemented.

4 Empirical results

The model and the equation (6) are estimated and calculated using the maximum likelihood estimation (MLE) and the BFGS quasi Newton algorithm coded in R. The results are shown in Sects. 4.1 and 4.2.

4.1 The transition intensity matrix results

Table 2 provides the estimated coefficients of the transition intensity matrix variables. We notice that most of the parameters that capture the effect of different channels, including direct channel and advertising channels, on transferring the consumer across the two different purchase intention states are statistically significant. In particular, direct type-in channel has negative effects on changing the consumers' purchase intention either from low to high or from high to low as revealed by the corresponding parameter coefficients (that is, $\beta_{12}^{d} = -0.3577$ and $\beta_{21}^{d} = -0.0123$). By contrast, advertising channels have positive effects on the

Table 2 The parameter estimation of the transition intensity matrix

Variables	Coefficients	Standard errors
Direct type-in (low, high) (β_{12}^{d})	−0.3577***	0.0491
Direct type-in (high, low) (β_{21}^{d})	−0.0123	0.0489
Brand paid search advertising (low, high) (β_{12}^{bp})	0.7321***	0.0652
Brand paid search advertising (high, low) (β_{21}^{bp})	0.1467**	0.0639
Generic paid search advertising (low, high) (β_{12}^{gp})	0.8277***	0.0954
Generic paid search advertising (high, low) (β_{21}^{gp})	0.2525**	0.0911
Brand organic search advertising (low, high) (β_{12}^{bo})	0.8960***	0.1354
Brand organic search advertising (high, low) (β_{21}^{bo})	0.1784	0.1335
Generic organic search advertising (low, high) (β_{12}^{go})	0.6383***	0.0563
Generic organic search advertising (high, low) (β_{21}^{go})	0.1974***	0.0546
SMS (low, high) (β_{12}^{s})	0.0359	0.1301
SMS (high, low) (β_{21}^{s})	0.7120***	0.1228
Email (low, high) (β_{12}^{e})	0.5190***	0.1360
Email (high, low) (β_{21}^{e})	0.5456***	0.1296
WeChat (low, high) (β_{12}^{w})	0.1410*	0.0698
WeChat (high, low) (β_{21}^{w})	0.5321***	0.0622
Affiliate programs (low, high) (β_{12}^{af})	0.4356*	0.2144
Affiliate programs (high, low) (β_{21}^{af})	0.2099	0.1751

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

transition of the consumer between two purchase intention states. We further elaborate on the various impacts under different channels below.

First, the direct type-in channel has a negative and statistically significant effect on transferring consumers from low purchase intention to high purchase intention, which indicates that consumers accessing the website through ad-avoidance channel will hardly raise their propensity to purchase. Direct type-in channel also has a negative but insignificant effect on transferring consumers from high purchase intention to low purchase intention, and the effect coefficient is very small ($\beta_{21}^{d} = -0.0123$), which to some extent reflects that consumers under ad-avoidance channel are more likely to reduce their purchase intention. Second, four search advertisings have positive effects on the transition on the consumer purchase intention, and with the exception of brand organic search advertising (high to low), all effects are statistically significant. More importantly, all four search advertisings have a greater impact on transferring consumers from low purchase intention to high purchase intention than on transferring consumers from high purchase intention to low purchase intention ($\beta_{12}^{bp} = 0.7321 > \beta_{21}^{bp} = 0.1467$, $\beta_{12}^{gp} = 0.8277 > \beta_{21}^{gp} = 0.2525$, $\beta_{12}^{bo} = 0.8960 > \beta_{21}^{bo} = 0.1784$, $\beta_{12}^{go} = 0.6383 > \beta_{21}^{go} = 0.1974$). This indicates that while search advertising can increase consumer purchase intention as well as decrease it, the enhancing effect is stronger. Among them, the enhancing effect of brand organic search advertising is the best, followed by generic paid search advertising, brand paid search advertising and generic organic search advertising ($\beta_{12}^{bo} = 0.8960 > \beta_{12}^{gp} = 0.8277 > \beta_{12}^{bp} = 0.7321 > \beta_{12}^{go} = 0.6383$). The reducing effect of generic paid search advertising is the strongest, followed by generic organic search advertising, brand organic search advertising and brand paid search advertising ($\beta_{21}^{gp} = 0.2525 > \beta_{21}^{go} = 0.1974 > \beta_{21}^{bo} = 0.1784 > \beta_{21}^{bp} = 0.1467$). Third, aside from affiliate programs, the effects of SMS, email, and WeChat advertising on the transition on consumers from high to low purchase intention are all greater than the effects on the transition on consumers from low to high purchase intention ($\beta_{21}^{s} = 0.7120 > \beta_{12}^{s} = 0.0359$, $\beta_{21}^{e} = 0.5456 > \beta_{12}^{e} = 0.5190$, $\beta_{21}^{w} = 0.5321 > \beta_{12}^{w} = 0.1410$, $\beta_{21}^{af} = 0.2099 < \beta_{12}^{af} = 0.4356$). With the exception of SMS (low, high) and affiliate programs (high, low), all effects are statistically significant. This indicates that while SMS, email, and WeChat advertising can increase consumer purchase intention as well as decrease it, the reducing effect is stronger. Among them, the enhancing effect of email advertising is the best, followed by affiliate programs, WeChat and SMS ($\beta_{12}^{e} = 0.5190 > \beta_{12}^{af} = 0.4356 > \beta_{12}^{w} = 0.1410 > \beta_{12}^{s} = 0.0359$). The reducing effect of SMS advertising is the strongest, followed by email, WeChat and affiliate programs ($\beta_{21}^{s} = 0.7120 > \beta_{21}^{e} = 0.5456 > \beta_{21}^{w} = 0.5321 > \beta_{21}^{af} = 0.2099$).

4.2 The state-dependent consumer behavior results

Figure 2 shows the transfer path of consumer purchase intention under nine channels. Consumers have two choices in each time period, that is remaining in the current hidden state or moving to another hidden state. The probability to purchase in state 1 (low purchase intention) of nine channels is 8.739%, 8.637%, 8.654%, 8.578%, 8.710%, 8.523%, 8.647%, 8.441% and 8.660%, respectively, and the probability to purchase in state 2 (high purchase intention) of nine channels is 55.168%, 55.213%, 55.216%, 55.211%, 55.190%, 55.251%, 55.198%, 55.282%, 55.190%, respectively (corresponding to parameter γ_j in Table 3). Table

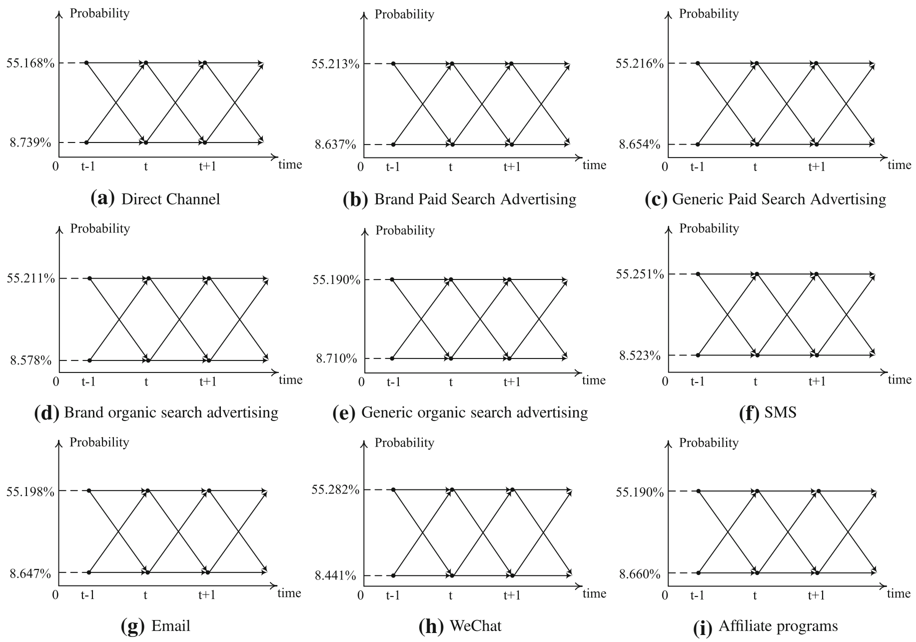

Fig. 2 The transfer path of consumer purchase intention

Table 3 Observed outcome sequence of different channels

Online channels	Observed outcome sequence	Parameter estimation	95% Confidence interval
Direct type-in	Y_{it}^{d}	$\gamma_1^d = -2.345880$	[−2.386914, −2.304839]
		$\gamma_2^d = 0.207446$	[0.186015,0.228874]
	V_{it}^{d}	$\mu_1^d = 0.010820$	[0.010727,0.010914]
		$\sigma_1^d = 0.008374$	[0.008295,0.008455]
		$\mu_2^d = 0.051424$	[0.050902,0.051946]
		$\sigma_2^d = 0.048571$	[0.048225,0.048919]
	$-2 * log - likelihood$	−469828.8	–
Brand paid search ads	Y_{it}^{bp}	$\gamma_1^{bp} = -2.358763$	[−2.400193, −2.317328]
		$\gamma_2^{bp} = 0.209274$	[0.187867,0.230698]
	V_{it}^{bp}	$\mu_1^{bp} = 0.010796$	[0.010703,0.010889]
		$\sigma_1^{bp} = 0.008358$	[0.008279,0.008438]
		$\mu_2^{bp} = 0.051353$	[0.050832,0.051873]
		$\sigma_2^{bp} = 0.048521$	[0.048177,0.048868]
	$-2 * log - likelihood$	−470149.2	–
Generic paid search ads	Y_{it}^{gp}	$\gamma_1^{gp} = -2.356671$	[−2.398148, −2.315199]
		$\gamma_2^{gp} = 0.209396$	[0.187976,0.230819]
	V_{it}^{gp}	$\mu_1^{gp} = 0.010802$	[0.010709,0.010895]
		$\sigma_1^{gp} = 0.008361$	[0.008282,0.008442]
		$\mu_2^{gp} = 0.051369$	[0.050848,0.051890]
		$\sigma_2^{gp} = 0.048534$	[0.048189,0.048882]
	$-2 * log - likelihood$	−469745.6	–
Brand organic search ads	Y_{it}^{bo}	$\gamma_1^{bo} = -2.366343$	[−2.408220, −2.324464]
		$\gamma_2^{bo} = 0.209196$	[0.187790,0.230576]
	V_{it}^{bo}	$\mu_1^{bo} = 0.010781$	[0.010688,0.010874]
		$\sigma_1^{bo} = 0.008344$	[0.008265,0.008424]
		$\mu_2^{bo} = 0.051288$	[0.050768,0.051808]
		$\sigma_2^{bo} = 0.048489$	[0.048145,0.048836]
	$-2 * log - likelihood$	−469738.5	–
Generic organic search ads	Y_{it}^{go}	$\gamma_1^{go} = -2.349590$	[−2.390695, −2.308485]
		$\gamma_2^{go} = 0.208333$	[0.186898,0.229766]
	V_{it}^{go}	$\mu_1^{go} = 0.010814$	[0.010720,0.010907]
		$\sigma_1^{go} = 0.008372$	[0.008292,0.008452]
		$\mu_2^{go} = 0.051410$	[0.050888,0.051932]
		$\sigma_2^{go} = 0.048558$	[0.048212,0.048906]
	$-2 * log - likelihood$	−469930.3	–

Table 3 continued

Online channels	Observed outcome sequence	Parameter estimation	95% Confidence interval
SMS	Y_{it}^{s}	$\gamma_1^s = -2.373367$	[−2.415717, −2.331023]
		$\gamma_2^s = 0.210836$	[0.189445,0.232234]
	V_{it}^{s}	$\mu_1^s = 0.010773$	[0.010680,0.010867]
		$\sigma_1^s = 0.008341$	[0.008261,0.008422]
		$\mu_2^s = 0.051254$	[0.050734,0.051774]
		$\sigma_2^s = 0.048472$	[0.048128,0.048819]
	$-2 * log - likelihood$	−469619.5	–
Email	Y_{it}^{e}	$\gamma_1^e = -2.357559$	[−2.399196, −2.315920]
		$\gamma_2^e = 0.208666$	[0.187248,0.230082]
	V_{it}^{e}	$\mu_1^e = 0.010799$	[0.010706,0.010892]
		$\sigma_1^e = 0.008357$	[0.008278,0.008438]
		$\mu_2^e = 0.051348$	[0.050826,0.051869]
		$\sigma_2^e = 0.048527$	[0.048188,0.048874]
	$-2 * log - likelihood$	−469427	–
WeChat	Y_{it}^{w}	$\gamma_1^w = -2.383932$	[−2.426837, −2.341035]
		$\gamma_2^w = 0.212056$	[0.190669,0.233442]
	V_{it}^{w}	$\mu_1^w = 0.010763$	[0.010669,0.010856]
		$\sigma_1^w = 0.008336$	[0.008257,0.008416]
		$\mu_2^w = 0.051178$	[0.050658,0.051698]
		$\sigma_2^w = 0.048443$	[0.048099,0.048789]
	$-2 * log - likelihood$	−469609.7	–
Affiliate programs	Y_{it}^{af}	$\gamma_1^{af} = -2.355816$	[−2.397405, −2.314228]
		$\gamma_2^{af} = 0.208370$	[0.186949,0.229790]
	V_{it}^{af}	$\mu_1^{af} = 0.010801$	[0.010707,0.010894]
		$\sigma_1^{af} = 0.008358$	[0.008278,0.008438]
		$\mu_2^{af} = 0.051359$	[0.050838,0.051881]
		$\sigma_2^{af} = 0.048531$	[0.048186,0.048879]
	$-2 * log - likelihood$	−469412.8	–

3 provides the results of observed outcome sequence of nine online channels, which can reflect the different consumer behavior of nine channels under two hidden purchase intention states.

It can be seen that consumers in state 2 have significantly more information collection behavior than those in state 1 ($\mu_2^d = 0.051424 > \mu_1^d = 0.010820$, $\mu_2^{bp} = 0.051353 > \mu_1^{bp} = 0.010796$, $\mu_2^{gp} = 0.051369 > \mu_1^{gp} = 0.010802$, $\mu_2^{bo} = 0.051288 > \mu_1^{bo} = 0.010781$, $\mu_2^{go} = 0.051410 > \mu_1^{go} = 0.010814$, $\mu_2^s = 0.051254 > \mu_1^s = 0.010773$, $\mu_2^e = 0.051348 > \mu_1^e = 0.010799$, $\mu_2^w = 0.051178 > \mu_1^w = 0.010763$, $\mu_2^{af} = 0.051359 > \mu_1^{af} = 0.010801$). This indicated that consumers will have more information collection behaviors when they have stronger purchase intention. We notice that in both state1 and state 2, consumers who access the website through ad-avoidance channel view more pages than those who access the website through advertising clicks ($\mu_1^d = 0.010820$, $\mu_2^d = 0.051424$), indicating that advertising does not enhance consumer information collection behavior and, to some extent, decreases consumer information collection behavior. And in advertising channels, consumers accessing the website through generic organic search advertising will view more web pages ($\mu_1^{go} = 0.010814$, $\mu_2^{go} = 0.051410$). More importantly, in both state 1 and state 2, consumers accessing the website through WeChat clicks have the least information collection behavior ($\mu_1^w = 0.010763$, $\mu_2^w = 0.051178$) and consumers accessing the website through SMS clicks have the penultimate least information collection behavior ($\mu_1^s = 0.010773$, $\mu_2^s = 0.051254$). Comparing with Table 2 we can find that the advertising effect of channels with little information collection behavior does not perform very well.

To sum up, from the perspective of state transition, we find that all eight types of online advertising have a positive impact on the transfer between different states of consumers, and most of them are statistically significant. In contrast, the direct type-in channel has a negative impact on the transfer of consumers, suggesting that direct type-in can not promote consumers to transfer from one state to another. Moreover, the results show that consumer-initiated advertising channels (searching advertising) have a stronger effect on enhancing consumer purchase intention than reducing it, while most firm-initiated advertising channels (SMS, WeChat, email) have a stronger effect on reducing consumer purchase intention than enhancing it. From state-dependent consumer behavior, we find that high purchase intention is accompanied by positive information collection behavior. In addition, we find that online advertising reduces consumer information collection behaviors to a certain extent by comparing with ad-avoidance channel. And the results show that online advertising channels with little information collection behavior do not perform well in transferring consumers from low purchase intention to high purchase intention. Our study enriches the literature on the evaluation of online advertising effectiveness by revealing the dynamic impact of online advertising on consumers' hidden states and by explaining why the effectiveness of online advertising varies across the online advertisement types.

5 Robustness checks

In order to avoid that the estimated result is a local optimal solution, different initial values need to be given to the model to ensure that the estimation has converged to a global optimum (Jackson, 2011). We have made the following adjustments to the initial values.

First, we change the initial values of the transition intensity. In Sect. 3 we posit that the transition intensity from low purchase intention to high purchase intention equals to the transition intensity from high purchase intention to low purchase intention, and the initial value of transition intensity is set to 0.25 (that is $q_{12} = q_{21} = 0.25$). In this section, we change the initial value of the transition intensity from 0.25 to 0.16, and from 0.25 to 0.5 (that is $q_{12} = q_{21} = 0.16$ and $q_{12} = q_{21} = 0.5$), the results remain unchanged. Then we posit that the transition intensity from high purchase intention to low purchase intention is greater than the transition intensity from low purchase intention to high purchase intention ($q_{12} = 0.16 < q_{21} = 0.25$). Subsequently, we assume that the transition intensity from low purchase intention to high purchase intention is greater than the transition intensity from high purchase intention to low purchase intention ($q_{12} = 0.25 > q_{21} = 0.16$). The results remain unchanged which show that the estimation has converged to a global optimum.

Second, we give different initial values to the emission matrix. In Sect. 3, we posit that consumers will have more information collection behaviors when they enhance their propensity to purchase, and the restriction $\mu_1 \leq \mu_2$ is implemented. In this section, we remove the restriction and change μ_1 and μ_2 from 0.006 and 0.03 to 0.05 and 0.02, respectively. Then we set different initial values for the probability of consumers to purchase (from $prob_1 = 0.3$, $prob_2 = 0.8$ to $prob_1 = 0.01$, $prob_2 = 0.7$ and $prob_1 = 0.5$, $prob_2 = 0.5$). The results remain unchanged which show that the estimation has converged to a global optimum.

In order to eliminate the influence of sample selection on the research results, we changed the sample selection range. We strict the condition for selecting consumers. In the paper, we retain only the data of consumers who visited the website more than seven times during the observation window. In this section, we give a more stringent condition for the selection of consumers. We change the times from seven to nine, that is we retain only the data of consumers who visited the website more than nine times during the observation window. Then, we give different initial values to the model to ensure that the estimation has converged to a global optimum, and finally get the results of the transition intensity matrix parameter estimation and the observed outcome sequence under different channels. The empirical results are provided in Tables 4 and 5.

A comparison of Table 4 with Table 2 reveals that the findings of Sect. 4.1 remain basically unchanged. But the effect of affiliate programs (low, high) on consumer transition is no more statistically significant. The reason may be that the number of consumers accessing the website through affiliate programs is relatively small after giving a more stringent condition for selecting consumers. A comparison of Table 5 with Table 3 reveals that the findings of Sect. 4.2 remain basically unchanged. Hence, our results remain robust.

Table 4 Robustness checks of the transition intensity matrix parameter estimation

Variables	Coefficients	Standard errors
Direct type-in (low, high) (β_{12}^{d})	– 0.4143***	0.0524
Direct type-in (high, low) (β_{21}^{d})	– 0.0776	0.0524
Brand paid search advertising (low, high) (β_{12}^{bp})	0.7658***	0.0683
Brand paid search advertising (high, low) (β_{21}^{bp})	0.2047**	0.0670
Generic paid search advertising (low, high) (β_{12}^{gp})	0.9618***	0.1030
Generic paid search advertising (high, low) (β_{21}^{gp})	0.3645***	0.0986
Brand organic search advertising (low, high) (β_{12}^{bo})	0.9386***	0.1407
Brand organic search advertising (high, low) (β_{21}^{bo})	0.2269	0.1394
Generic organic search advertising (low, high) (β_{12}^{go})	0.6989***	0.0597
Generic organic search advertising (high, low) (β_{21}^{go})	0.2651***	0.0580
SMS (low, high) (β_{12}^{s})	0.0936	0.1442
SMS (high, low) (β_{21}^{s})	0.7777***	0.1364
Email (low, high) (β_{12}^{e})	0.3959**	0.1416
Email (high, low) (β_{21}^{e})	0.4461***	0.1356
WeChat (low, high) (β_{12}^{w})	0.1917**	0.0774
WeChat (high, low) (β_{21}^{w})	0.6318***	0.0695
Affiliate programs (low, high) (β_{12}^{af})	0.2779	0.2381
Affiliate programs (high, low) (β_{21}^{af})	0.0042	0.1940

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 5 Robustness checks of observed outcome sequence of different channels

Online channels	Observed outcome sequence	Parameter estimation	95% Confidence interval
Direct type-in	Y_{it}^{d}	$\gamma_1^d = -2.277383$	[− 2.321106, − 2.233663]
		$\gamma_2^d = 0.285429$	[0.261704,0.309155]
	V_{it}^{d}	$\mu_1^d = 0.010923$	[0.010822,0.011024]
		$\sigma_1^d = 0.008393$	[0.008307,0.008480]
		$\mu_2^d = 0.051638$	[0.051061,0.052216]
		$\sigma_2^d = 0.048468$	[0.048089,0.048849]
	$-2 * log - likelihood$	− 402318.1	–
Brand paid search ads	Y_{it}^{bp}	$\gamma_1^{bp} = -2.291441$	[− 2.335685, − 2.247196]
		$\gamma_2^{bp} = 0.287132$	[0.263450,0.310815]
	V_{it}^{bp}	$\mu_1^{bp} = 0.010894$	[0.010793,0.010995]
		$\sigma_1^{bp} = 0.008372$	[0.008287,0.008459]
		$\mu_2^{bp} = 0.051547$	[0.050972,0.052123]
		$\sigma_2^{bp} = 0.048409$	[0.048031,0.048789]
	$-2 * log - likelihood$	− 402563.5	–
Generic paid search ads	Y_{it}^{gp}	$\gamma_1^{gp} = -2.286723$	[− 2.330836, − 2.242608]
		$\gamma_2^{gp} = 0.287941$	[0.264227,0.311654]
	V_{it}^{gp}	$\mu_1^{gp} = 0.010910$	[0.010808,0.011011]
		$\sigma_1^{gp} = 0.008384$	[0.008298,0.008471]
		$\mu_2^{gp} = 0.051596$	[0.051020,0.052173]
		$\sigma_2^{gp} = 0.048439$	[0.048061,0.048821]
	$-2 * log - likelihood$	− 402294	–
Brand organic search ads	Y_{it}^{bo}	$\gamma_1^{bo} = -2.298097$	[− 2.342753, − 2.253442]
		$\gamma_2^{bo} = 0.287065$	[0.263402,0.310728]
	V_{it}^{bo}	$\mu_1^{bo} = 0.010881$	[0.010780,0.010982]
		$\sigma_1^{bo} = 0.008360$	[0.008274,0.008447]
		$\mu_2^{bo} = 0.051487$	[0.050912,0.052062]
		$\sigma_2^{bo} = 0.048379$	[0.048002,0.048759]
	$-2 * log - likelihood$	− 402259.4	–
Generic organic search ads	Y_{it}^{go}	$\gamma_1^{go} = -2.280090$	[− 2.323829, − 2.236351]
		$\gamma_2^{go} = 0.286654$	[0.262924,0.310384]
	V_{it}^{go}	$\mu_1^{go} = 0.010921$	[0.010820,0.011022]
		$\sigma_1^{go} = 0.008394$	[0.008308,0.008481]
		$\mu_2^{go} = 0.051634$	[0.051057,0.052211]
		$\sigma_2^{go} = 0.048462$	[0.048083,0.048844]

Table 5 continued

Online channels	Observed outcome sequence	Parameter estimation	95% Confidence interval
	$-2*log-likelihood$	-402415.6	–
SMS	Y_{it}^{s}	$\gamma_1^s = -2.302777$	[-2.347807, -2.257747]
		$\gamma_2^s = 0.288677$	[0.264999,0.312355]
	V_{it}^{s}	$\mu_1^s = 0.010879$	[0.010777,0.010980]
		$\sigma_1^s = 0.008361$	[0.008275,0.008448]
		$\mu_2^s = 0.051467$	[0.050891,0.052042]
		$\sigma_2^s = 0.048371$	[0.047994,0.048752]
	$-2*log-likelihood$	-402138.2	–
Email	Y_{it}^{e}	$\gamma_1^e = -2.286580$	[-2.330822, -2.242343]
		$\gamma_2^e = 0.286492$	[0.262787,0.310196]
	V_{it}^{e}	$\mu_1^e = 0.010905$	[0.010804,0.011006]
		$\sigma_1^e = 0.008378$	[0.008292,0.008465]
		$\mu_2^e = 0.051575$	[0.050999,0.052152]
		$\sigma_2^e = 0.048431$	[0.048052,0.048812]
	$-2*log-likelihood$	-401981.1	–
WeChat	Y_{it}^{w}	$\gamma_1^w = -2.318329$	[-2.364217, -2.272441]
		$\gamma_2^w = 0.290677$	[0.267019,0.314335]
	V_{it}^{w}	$\mu_1^w = 0.010860$	[0.010759,0.010961]
		$\sigma_1^w = 0.008352$	[0.008266,0.008438]
		$\mu_2^w = 0.051351$	[0.050777,0.051926]
		$\sigma_2^w = 0.048324$	[0.047948,0.048703]
	$-2*log-likelihood$	-402174.4	–
Affiliate programs	Y_{it}^{af}	$\gamma_1^{af} = -2.284103$	[-2.328255, -2.239950]
		$\gamma_2^{af} = 0.286018$	[0.262310,0.309725]
	V_{it}^{af}	$\mu_1^{af} = 0.010908$	[0.010806,0.011009]
		$\sigma_1^{af} = 0.008378$	[0.008293,0.008465]
		$\mu_2^{af} = 0.051593$	[0.051016,0.052170]
		$\sigma_2^{af} = 0.048437$	[0.048059,0.048819]
	$-2*log-likelihood$	-401974.4	–

6 Discussion

In this study, we explore the dynamic impacts of nine different online channels on the transition of consumers' potential purchase propensity and the consumer behavior under two hidden states. To examine our research questions, we construct a consumer purchase intention transfer dynamic model by using CT-HMM to capture the transfer path of consumers who are affected by various online channels. Consistent with previous literature (Sridhar et al., 2016; Hoban and Bucklin, 2015), our findings reveal that online advertising can have a positive impact on consumers. However, after considering the impact of online advertising on the dynamic changes of consumers' potential states which was ignored by most studies of online advertising effectiveness, we find that online advertising not only promotes the transfer of consumers from low purchase intention to high purchase intention, but also significantly promotes the transfer of consumers from high purchase intention to low purchase intention. Therefore, taking online advertising as a marketing means is a double-edged sword.

Our study shows that the eight different types of online advertising have various effects on the transition of consumer purchase intention. We explore that search advertising can significantly increase consumers' propensity to purchase, and its effect on reducing consumer purchase intention is not very strong in comparison. The reason may be that search advertising is a type of online advertising based on consumer-initiated contacts, and consumers have a certain degree of active choice over such advertisements, so they are relatively less likely to be annoyed. The influence of SMS on consumers' transition from low purchase intention to high purchase intention is very small and even insignificant, however, the influence on the transition from high purchase intention to low purchase intention is relatively large and significant. This implicates that consumers have a very low annoyance threshold to SMS advertising, and they are easy to get tired of SMS advertising and reduce their purchase intention. Since consumers become more conscious of personal privacy issues, SMS advertising may no longer be an effective online advertising model. More importantly, we find that advertisements such as email and WeChat also play a stronger role in reducing consumers' purchase intention than in improving consumers' purchase intention. In addition, affiliate programs, as search advertising, have a strong promotion effect, but the effect is not as good as search advertising. The results explore that advertisements initiated by firms are more likely to cause consumer discontent, however the dissatisfaction will be somewhat reduced when consumers do not contact with the company directly, but through a third-party website. Apart from analyzing the dynamic impacts of different online channels on the transition of consumer purchase intention, this paper also reveals the different consumer behaviors of various online advertising under two hidden states. Our study shows that although online advertising has a positive effect on the transition of hidden purchase intention, it can not increase consumers' information collection behavior, and to some extent even decreases the information collection behavior. The reason may be that the advertisement itself already conveys part of the product information to consumers when it contacts them, so consumers will accordingly reduce information collection behavior during the purchase process. Furthermore, consumers are more likely to enhance their information collection behavior when they raise the propensity to purchase. We explore that advertisements which can not improve consumer purchase intention very well have fewer stimulating effects on consumers' information collection behavior than other advertisements.

The main contribution of our research is that we reveal the dynamic impact of online advertising on consumers' potential states, and our results directly reflect the extent to which different advertisements promote consumer purchase and cause consumer irritation, thus helping enterprises to better explore potential consumers as well as avoid causing consumer aversion. By studying the hidden state, we can more clearly capture the dynamic impact mechanism of each advertisement on the internal transfer of consumers, rather than simply evaluating the effectiveness of advertisements in terms of click-through rates and sales. Therefore, we can better explain why some advertisements promote consumer purchase, while others reduce consumer purchase. Furthermore, by evaluating and comparing nine different channels, we can better identify the role of various types of advertising and help enterprises to choose the appropriate online advertisements to place at different stages. The study has some important managerial implications. First, in paid search advertising, enterprises should focus more on investing in generic rather than brand search advertising. However, in organic search advertising, enterprises need to pay more attention on optimizing their natural rankings under brand keywords rather than generic keywords. Second, most firm-initiated advertisements have a greater reducing impact on consumer purchase intention than promoting impact. Therefore, enterprises can place such advertisements in the early stage to develop a contact with consumers but should not place too many channels in order to avoid making consumers feel that their privacy has been violated. Third, each advertising leads to a different consumer information collection behavior, and if enterprises want to encourage new consumers (with low purchase intention) to actively learn more product information, placing email and affiliate programs on them may be more suitable.

There are some limitations and future research directions in our study. For instance, due to the protection of consumers' personal information, the data specific to individual consumer characteristics is not taken into account in the model. In addition, we have not considered the effect of the number of advertising clicks on the transition of consumer purchase intention. In the future, we can explore whether the change of advertising clicks will affect the transfer of consumers' potential purchase intention, and what range of clicks has the best positive transfer effect on consumer purchase intention.

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Data availability The data analysed during the current study are not publicly available as they contain confidential enterprise data that the authors acquired through a license. Information on how to obtain the data is available from the corresponding author upon reasonable request.

Declarations

Conflict of interest The authors declare no conflict of interest.

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