Telematics and Informatics xxx (xxxx) xxxx

Contents lists available at ScienceDirect

Telematics and Informatics

journal homepage: www.elsevier.com/locate/tele

Free contents vs. inconvenience costs: Two faces of online video advertising

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ARTICLE INFO

Keywords:
Online video platform
Online video advertising
Inconvenience cost
Mixed logit
Simulation
Market share
Conjoint survey

ABSTRACT

With the growth of online video platforms such as *YouTube* and *Netflix*, not only the video content market, but also the online video advertising market are growing rapidly. However, as the video content industry expands, the inconvenience caused by video advertisements is increasing, leading to ad-blocking by consumers. To identify the causes of ad-blocking, this study collects consumer preference data using a conjoint survey and estimates the inconvenience cost of advertisements using a mixed logit model. In addition, we performed computational experiments by changing advertising attributes to identify strategies for increasing the market share of online video platform companies. Our results show that the use of personal information affects consumers most seriously, and that platforms can increase market share by reducing the length of advertisements, by reducing the use of personal information, or by blocking all advertising.

1. Introduction

Netflix was a latecomer in the digital versatile disc (DVD) rental market, but it is now a leading innovator in the media content and online platform industries (Burroughs, 2019; Lobato, 2019; Shattuc, 2020). *Netflix* introduced the paid subscription model to the over-the-top (OTT) service market and succeeded in the business model that provides professional content such as movies and TV shows over the Internet without advertising (Matrix, 2014; McCord, 2014; McDonald and Smith-Rowsey, 2016). Most other Internet platforms including *YouTube* are originally characterized by a two-sided model consisting of advertisers that pay to advertise on the platform and consumers that consume content, including advertisements, for free. However, recently, *YouTube* also began to provide premium services for paid subscribers, offering subscribers benefits such as ad-free content, offline storage, and unlimited music listening. The paid services provided by global video platforms also affect other platform companies that have recently entered the market (i.e., *Disney+*, *AT&T*, *Apple*) or are already competitors (i.e., *Hulu*, *Amazon*). After all, innovation on one side has positive spillover effects on the entire ecosystem, leading to the spread of innovation (Acs et al., 2009; Han et al., 2012).

Consumers respond positively when platforms offer content without advertisements, despite having to pay for it (Anderson and Gans, 2011; Johnson, 2013). This phenomenon is caused by consumer perception of advertisements as annoying due to the platform company's indiscriminate advertisement provision and excessive competition among advertisers (Anderson and Gans, 2011; Choi, 2015; Tåg, 2009). In the personal computer (PC) environment, it is possible for consumers to consume other content while video advertisements are playing. In the mobile environment, however, consumers are unable to consume other content while video

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https://doi.org/10.1016/j.tele.2020.101476
Received 1 March 2020; Received in revised form 14 July 2020; Accepted 23 July 2020
0736-5853/

advertisements are being served, so the inconvenience suffered by consumers is greater than in the PC environment. As a result, consumers endeavor to reduce the inconvenience of advertising using ad-blocking programs such as Adblock Plus that can be easily downloaded from the Internet (Anderson and Gans, 2011; Redondo and Aznar, 2018; Vratonjic et al., 2013). Development of the Internet environment and proliferation of smart devices have increased the opportunities for consumers to access the Internet and consume content without time and space constraints. However, the growing number of consumers using ad-blocking programs on smartphones and PCs illustrates problems with the current Internet environment dominated by excessive advertisements (Iqbal et al., 2017; Vallade, 2008).

Adblock Plus is a representative ad-blocking program that was developed in 2009 and has grown into the most popular ad-blocking program in the world. Ad-blocking programs leverage the right of consumers to block annoying advertisements but are perceived as a problem by content providers because they block all advertisements, not only annoying ones. Internet platform companies that generate profits by relying on advertisements based on user traffic may encounter difficulties due to proliferation of ad-blocking programs. In the end, the Internet ecosystem will require a new value chain structure (Ertz and Sarigöllü, 2019; Klym and Clark, 2019). To ensure stable revenue, platform companies will charge for services and provide them only to subscribed users (Klym and Clark, 2019; Sanson and Steirer, 2019). While a closed Internet environment can sustain certain levels of quality and stable growth, it will prevent content and services from being shared and used freely, which will hinder the innovative growth of the content industry and related ecosystem (Lee et al., 2015a,b). In particular, for platform companies that grow through network externality effects, a closed environment may reduce the amount of information and opportunities for user participation, which will lead to decreases in Internet traffic. Arthur (1989), Hagiu (2006), Katz and Shapiro (1994) argue that these factors will have negative impacts on the Internet ecosystem ultimately.

Providing the appropriate amount of advertising will reduce consumer inconvenience and be a good success strategy for companies. At the same time, identifying the appropriate amount of advertising will be an important foundation for virtuous cycle structures in the Internet market. According to previous studies, the excess of advertising in the Internet platform environment is quite serious, problems are ongoing, and consumers use ad-blocking services without hesitation (Anderson and Gans, 2011; Tåg, 2009). Some previous studies examined inconvenient attributes of advertisements but failed to deduce the economic value of such attributes (Baek and Morimoto, 2012; Cho and Cheon, 2004; Elliott and Speck, 1998). The present study identifies aspects of advertising that are most inconvenient to consumers and assesses their level of inconvenience. In particular, this study aims to derive the inconvenience costs of online video advertising, for which the growth rate is fast and advertisement efficiency is high. Assuming a virtual ad-blocking service, we measure the inconvenience cost of advertisements to consumers through this service. This virtual ad-blocking service is constructed by including representative features of current online video advertising. Additionally, we analyze changes in platform market share according to consumer preferences when new companies enter the competitive video platform market and when existing companies change the characteristic factors of their advertising. The results of this study can be used to formulate hypothetical strategies to satisfy the utility needs of consumers and increase market share through advertising, which is an important source of income for online platform companies.

This paper is composed as follows. Section 2 reviews previous literature and outlines the research background. Section 3 explains the methodology and model used for estimating the inconvenience costs of online video advertising and discusses the market shares of online platform companies. Section 4 describes the questionnaire data analyzed in this study. Section 5 outlines the results of analyses using our model. Section 6 summarizes the major issues arising in the course of the research, and discusses the implications of the results.

2. Literature review and research background

The increasing number of consumers using ad-blocking programs is explained by consumer desire to avoid unnecessary use of consumer resources (attention) and rational behavior by consumers attempting to find satisfaction and profit using their own attention and time (Davenport and Beck, 2001; Goldhaber, 1997; Vallade, 2008). The attention economy model proposed by Goldhaber (1997) interprets the value of information as an economic concept. That some information is valuable means that people consume information by “paying attention.” On the contrary, information is useless when is does not attract attention. Humans have limited time, thought, and sensory organs to devote to paying attention and feel increasingly tired and bored as the duration of attention increases. Therefore, the quality of attention paid will decrease (Terranova, 2012). In other words, as advertisement-related information increases, consumers become less and less able to accept new information, become more easily worn out, and more likely to avoid or to refuse to view advertisements rather than finding value in them.

Some people consume advertisements without discomfort, and some people feel that advertisements interfere with their behavior and are unnecessary. This is because there are individual differences in the standards used to determine profit and loss associated with online advertisements, and the sensitivity to inconvenience among individuals is different (Kahneman and Tversky, 2013). It is not easy to express the psychological costs of individual consumers as a single economic unit because they are latent costs that are not revealed unless individuals directly express them (Naous and Legner, 2019; Shin et al., 2015, 2016). Therefore, it is necessary to estimate the inconvenience costs of advertisements according to individual consumers’ tendencies.

Previous research addressed the competitive relationships between consumers and advertisers in the platform industry in the context of two-sided markets. Rysman (2004) examined Yellow Pages advertisements, Kaiser and Wright (2006) studied magazine advertisements, and Wilber (2008) analyzed television advertisements. Choi (2015), Anderson and Gans (2011), and Tåg (2009) analyzed the effects of ad-blocking on the platform ecosystem. According to Anderson and Gans (2011) and Tåg (2009), the proliferation of ad-blocking programs means that more consumers are becoming sensitive to advertisements, but also that advertisers are likely to increase the number of advertisements and increase profits based on those consumers who are less sensitive to advertisements. However, in the end, increases in advertisements will increase the number of consumers who feel uncomfortable with advertisements, and the proliferation of ad-blocking programs will reduce platform profits and lower platform quality (Anderson and Gans, 2011; Tåg, 2009). Ad-blocking programs will proliferate when platform content quality is reduced, consumer rejection of advertisements increases, and advertiser profits decrease. Paradoxically, ad-blocking programs can increase the number of advertisements and advertising revenue. On the other hand, Choi (2015) performed an empirical analysis of Korean Internet portals and showed that, as the number of people blocking advertisements increases, the value of consumers who do view advertisements increases, and the amount of advertisements decreases. Therefore, previous research focused on finding the balance point of ecosystems by examining changes in the number and effect of advertisements, under the assumption that ad-blocking programs will spread. However, they did not take into account the reasons that consumers opted to use ad-blocking programs or the inconvenience experienced by individual consumers, which are among causes of change in consumption patterns. In addition, previous studies are affected by limitations, such as a failure to estimate inconvenient attributes according to economic value, and to prospect platform market share according to advertising strategy.

Among previous online advertising studies, many seek to identify factors that have significant effects on the efficiency of advertisements. Some studies analyzed the inconvenience of advertisements using consumer personal information (Awad and Krishnan, 2006; Hoofnagle et al., 2012a,b; Phelps et al., 2000; Tucker, 2012). Others investigated the inconvenience caused by repeated playback of similar advertisements (Kim, 2018; Lee and Cho, 2010; Schmidt and Eisend, 2015), the effectiveness of advertisements according to length (Goodrich et al., 2015; Newell and Henderson, 1998; Schmidt and Eisend, 2015), preferences for advertisements that consumers can skip (Belanche et al., 2017; Joa et al., 2018; Vallade, 2008), and the effectiveness of advertisements according to location (Li and Lo, 2015; Mei et al., 2010). Previous studies also analyzed factors affecting online video advertising, which has increased rapidly since 2010 (Hsieh et al., 2012; Lee and Lee, 2011; Lee et al., 2013), and ways to increase the efficiency of online video advertising (Mei et al., 2007; Zhang, et al., 2017).

Online advertising is developing and expanding but can be interpreted as a problem in society due to inconvenience to consumers. In this study, we examined problems associated with the impact of advertising on consumers and society by referring to previous research that investigated inconvenience associated with online advertisements (Baek and Morimoto, 2012; Cho and Cheon, 2004; Elliott and Speck, 1998) and that estimated the social costs of spam email (Kim et al., 2006; Yoo, et al., 2006).

3. Methodology

In this study, we chose to apply a mixed logit model from among discrete choice models (McFadden, 1973; Train, 2009). Commonly used discrete choice models such as logit and probit models assume that all consumers have the same preference for a particular good or service. On the other hand, in mixed logit models, consumers may have heterogeneous preferences, and the researcher can set different distributions for the coefficients of each attribute. Discrete choice models are widely used to analyze consumer preferences for information and communication technology (ICT) products or services (Shin et al., 2014; Lee et al., 2015; Shin et al., 2016). In discrete choice models, it is assumed that each consumer i has a utility function related to each product or service j in the choice set t (McFadden, 1973; Train, 2009). The utility function is expressed as Eq. (1).

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} = \sum_{k} \beta'_{ik} X_{jkt} + \varepsilon_{ijt} \tag{1}$$

U_{ijt} represents the indirect utility when respondent i chooses alternative j of the t^{th} alternative set, where utility consists of deterministic utility $V_{ijt}$and stochastic utility ε_{ijt}. The deterministic utility part consists of a vector X_{jkt}comprising attributes related to product j in alternative set t and a vector β_{ik} representing the coefficient of each attribute k. β_{ik} is a multivariate normal distribution with mean b and covariance matrix W, and $\varepsilon_{ijt}$is defined as an I-type extreme value distribution. In this utility structure, the consumer chooses an alternative that maximizes utility. Thus, based on the utility function, we can derive the choice probability of consumer i choosing alternative j in set t is given by Eq. (2)

$$P_{ijt} = \int \frac{e^{V_{ijt}(\beta)}}{\sum_k e^{V_{ikt}(\beta)}} f(\beta) d\beta \tag{2}$$

The choice probability of the mixed logit model as shown in Eq. (2) should be approximated through sufficient simulation (Train, 2009). The maximum likelihood estimation (MLE) method is used to estimate the parameter β of the multinomial logit model, while the mixed logit model requires simulated maximum likelihood estimation (SMLE) (Train, 2009; McFadden and Train, 2000). An approximate value can be obtained by arbitrarily extracting the S number of beta values β $(=\beta^{(s)})$, and the log likelihood function (lnSL) of Eq. (3) can be obtained through simulation.

$$\ln SL = \sum_{i=1}^{N} \sum_{j=1}^{J} Y_{ij} \ln \left\{ \frac{1}{S} \sum_{s=1}^{S} \frac{\exp[\beta^{(s)'} Z_{ij}]}{\sum_{k \in C_i} \exp[\beta^{(s)'} Z_{ik}]} \right\} \tag{3}$$

where N is the total number of respondents, and the choice result for optional alternative j of the individual respondent i is 1 if selected and 0 if not selected. In this study, applying the SMLE method to Eq. (3) yields estimates of the required parameters. The parametric estimation method used in the SMLE method is the same as the MLE of the multinomial logit model but differs in that it uses the simulation choice probability and is asymptotically efficient with consistency and follows the normal distribution asymptotically (McFadden and Train, 2000).

The bias of the SMLE decreases in proportion to the variance of the simulation that computes the choice probability. Therefore, if the number of simulations is increased, the variance of the simulation choice probability decreases; accordingly, the bias of the SMLE is also reduced. According to previous studies, the bias is negligible when the number of simulations is about 250 (Brownstone and Train, 1998). In the present study, we used 500 repetitions with reference to previous research.

The coefficient values obtained through estimation represent the marginal contribution of each attribute with arbitrary units to utility, so it is difficult to compare the effects of each attribute. Therefore, it is necessary to calculate the marginal willingness-to-pay (MWTP) for each attribute from the estimation results. To analyze the economic value of individual attributes, the MWTP for each attribute k can be derived as Eq. (4). The MWTP is called the compensation value in microeconomics and is the amount that can be offset by changing one unit of the attribute k and can be interpreted as a change in the compensated surplus of the consumer when the attribute is changed. Relative importance (RI) of the individual attribute k can be derived from the samples derived in the simulation process. The RI for each attribute may be analyzed as part-worth. The part-worth of the attribute k can be calculated by multiplying the difference between the maximum level and minimum level of the attribute k by the estimated coefficient value β_k. In the N derived samples, the average RI can be calculated using Eq. (5).

$$\text{Median } \; MWTP_k = Median_i\left[-\frac{\frac{\partial U_i}{\partial x_i}}{\frac{\partial U_i}{\partial p_i}}\right] = Median_i\left[-\frac{\beta_{ik}}{\beta_{i(price)}}\right] \tag{4}$$

$$\text{(Average Relative Importance Percent of Attribute k)} = \frac{1}{N}\sum_{n=1}^{N}\left(\frac{part-worth_{nk}}{\sum_k part-worth_{nk}} \times 100\right)$$

$$where,\; part-worth_{nk} = (intervalofattributek's levle) \times \beta_{nk} \tag{5}$$

Forecasts of future market share due to changes in the strategies of online video platform companies can be calculated based on the coefficient β_i derived from estimation. If consumer i averages the probability of choosing alternative j by all consumers N, the average choice probability of each alternative j can be obtained as in Eq. (6).

$$S_j = \sum_i\left[\int \frac{\exp(\beta_i' x_j)}{\sum_k \exp(\beta_i' x_k)} f(\beta)d\beta\right]/N \tag{6}$$

4. Survey and data

Pilot tests were conducted in advance of the questionnaire used in this study. We identified 117 valid samples during the period from December 25 to December 31, 2018. Based on a pilot analysis, we revised the questionnaires and used them in our main survey. The main survey was conducted online by a specialized survey company among 500 ordinary consumers (20–59 years old) residing in 17 regions including special cities, metropolitan cities, special self-governing cities, provinces, and special self-provinces in South Korea from January 13 to February 14, 2019. The survey was aimed at users of platforms that offer free content with advertisements.

The demographic characteristics of respondents to the questionnaire are shown in Table 1.

The questionnaire consisted of two parts. The first included questions about current Internet usage, video content consumption behavior, and demographic information such as sex, age, and occupation. The second part included responses regarding consumers' preferences about detailed functions of ad-blocking services targeting a conjoint card, composed of a conjoint analysis method. Those who answered the survey reported consuming video content more than once a week. Average respondents consumed 6 videos per day and spent 58 min a day viewing content.

Conjoint analysis is a way of collecting information about consumer preferences for virtual goods composed of various attributes (Green and Srinivasan, 1978, 1990). Conjoint analysis has been widely used for demand analysis in marketing (Ben-Akiva et al., 2019; Shin et al., 2015; Troiano et al., 2019) and to study new information and communication technology (ICT) products (Danaf et al., 2019; Maeng et al., 2020; Shin et al., 2014, 2016). Previous studies also estimated inconvenience costs for consumers using preference statements addressing the degree of inconvenience associated with services or products and the cost of conversion (e.g. Kim et al., 2015; Lee, et al. 2006; Lee et al., 2017). Conjoint analysis is a method in which a consumer chooses the most desirable combination of attribute cards to maximize utility given a limited budget. Selected products always have higher utility than non-selected products. It is also possible to analyze the preferences of consumers in advance by analyzing attributes of new products or services to be released under the assumption of actual market conditions (Green and Srinivasan, 1978, 1990).

Based on previous conjoint analysis research, this study estimates the effects of inconvenient factors constituting online video advertisements and analyzes economic value based on the results of estimating each attribute. Therefore, we estimated the inconvenience costs that consumers feel as a result of advertising.

Table 2 shows a virtual online video ad-blocking service composed of six attributes used to estimate the inconvenience costs caused by online video advertising. As the number of attributes increases, respondents may find it difficult to choose; therefore, we limited the number of attributes to six. We assumed that other features such as platform, quality of service, and service-enabled devices were identical in effect.

Table 1
Demographic characteristics of the respondents.

		# of respondents	Ratio (%)
Total		500	100
Sex	Male	248	49.6
	Female	252	50.4
Age (years)	20–29	128	25.6
	30–39	128	25.6
	40–49	128	25.6
	50–59	116	23.2
Average monthly telecommunication fee (10,000 KRW)[1]	1–3	164	32.8
	4–6	201	40.2
	7–9	82	16.4
	10–20	50	10
	Over 20	3	0.6
Unlimited data services	Subscription	231	46.2
	None	269	53.8
Average video content views per day (average #: 6)	Under 2	101	20.2
	3–5	237	47.4
	6–10	120	24
	Over 10	42	8.4
Average video content view time per day (average, 58.9 min)	Under 10	51	10.2
	11–20	63	12.6
	21–30	93	18.6
	31–40	36	7.2
	41–50	36	7.2
	51–60	100	20
	61–99	36	7.2
	Over 100	85	17

[1] 1USD is 1205 KRW (Korean Won) as of March 2, 2020.

Table 2
Attributes and attribute levels of online video ad-blocking services.

Attribute	Explanation and level
Behavioral ad-blocking	Behavioral ad-blocking function according to degree of personal information utilization
	① Block behavioral ads with high privacy
	② Block behavioral ads with low privacy
	③ Block all behavioral ads
	④ Do not use
Repeated ad-blocking	Repeated ad-blocking function
	① Use
	② Do not use
Ad-blocking by length	Ad-blocking function by ad length
	① Block ads longer than 5 s
	② Block ads longer than 10 s
	③ Block ads longer than 15 s
Ad-blocking by location	Ad-blocking function by ad location; ads can be inserted before, middle, and after video content playback
	① Block "before" ads
	② Block "before" and "middle" ads
	③ Block "before" "middle" and "after" ads
	④ Do not use
Ad-blocking by skippability	Ad-blocking function according to skip button generation
	① Block skippable ads
	② Block non-skippable ads
	③ Do not use
Monthly fee (1000 KRW)[2]	Monthly cost of an ad-blocking service
	① 2
	② 4
	③ 6
	④ 8

[2] [1] USD is 1205 KRW (Korean Won) as of March 2, 2020.

Advertisements in traditional media, such as TV and radio, are mostly mass marketing tools. With the development of the Internet, one-to-one marketing has become possible based on information collected about individual characteristics and behaviors. Advertisers are using these individual characteristics and behaviors for targeted advertising. This is called online behavioral advertising (Boerman et al., 2017). Online behavioral advertising can have privacy infringement problems inherent to collecting, analyzing, and utilizing behavioral information about individuals in real time. Consumer preferences addressing the inconvenience of online video advertising will vary depending on the degree of personal information utilization. The virtual service attributes of this study are set to block behavioral advertisements using high levels of personal information, block behavioral advertisements using low levels of personal information, and block all behavioral advertisements using personal information (Boerman et al., 2017; Chen and Stallaert, 2014; Goldfarb and Tucker, 2011). Advertising also attempts to attract consumer attention through repetition. However, consumers will be more likely to feel uncomfortable as unwanted advertisements repeat (Kim, 2018; Lee and Cho, 2010; Schmidt and Eisend, 2015). To analyze this, the repeat ad-blocking function was inserted in the virtual service attributes.

Online video advertisements can be located before, in the middle, or after video playback. These advertisements provide information regarding the default watching time for consumers and can also include a skip button to avoid advertising. Since there are various advertisement lengths, the length of the advertisements included in the study were based on existing research and the average advertisement length of representative platforms for market share 1 or 2 (Campbell et al., 2017; Krishnan and Sitaraman, 2013; SociallySorted, 2018). The 'Monthly fee' attribute is calculated based on the ad-blocking services registered in the Google/Apple App store. There are many ad-blocking apps and the price of them among paid apps varied from 1000 to 9900 won. After excluding the lowest and highest prices, 'monthly fee' was selected as 2000, 4000, 6000, and 8000 and measured as a continuous variable. We included attributes and levels to investigate the relative importance of each function constituting the ad-blocking service and determined how they affected the value that consumers perceive.

There is a total of 1152 ($=4 \times 2 \times 3 \times 4 \times 3 \times 4$) configurable conjoint card combinations based on six attributes for each level. However, respondents are overburdened when they are asked to answer all cases. Therefore, each card needs to be configured so that the balance of attributes is well distributed and the correlations between the attributes are minimized. In this study, we used the optimal design method, D-efficiency, using the *R* program, so that the standard error between attributes is minimized. Among the balanced designs with a D-efficiency of 1, 48 alternative cards were selected and divided into 16 sets with no overlapping attributes. A choice set consisted of a total of four cards with three normal cards and a 'No choice' card. As a result, a total of 16 choice sets were created. The final 16 choice sets were divided into four combinations, so that one respondent could be randomly assigned 1 combination. Respondents can answer in order of preference from the four options of choice and respond to a total of four choice sets. A sample card is shown in Table 3.

5. Results

The analysis model used in this study is divided into two parts. The first part estimates the consumers' preferences for attributes that constitute the video ad-blocking service and analyze the MWTP and the RI. The second part predicts the changes of market share of each platform using computational experiments 1) when the attributes of the video advertisements on the specific platform are changed based on the derived consumer preferences and 2) when new platform companies with different advertising strategies enter the market.

5.1. Consumer preferences for ad-blocking services

First, the attributes of "behavioral ad-blocking," "repeat ad-blocking," and "ad-blocking by skippability" were estimated with the "Do not use" attribute as a reference attribute. In addition, the attributes of "ad-blocking by length," "ad-blocking by location," and "monthly fee" were analyzed using continuous variables.

Table 4 shows the mean and variance of each attribute coefficient that determines consumer preference. As a result of analysis, the mean of all the attributes was significant with a confidence interval of 5%. "Block all behavioral ads" was the highest coefficient, and "ad-blocking by length" was the lowest coefficient among the characteristics of the advertisements. In particular, the coefficients of the "ad-blocking by length" and "monthly fee" attributes were negative; that is, consumers preferred shorter advertisements and lower prices. In the case of variance, the heterogeneity of all attributes except for "block all behavioral ads," and "ad-blocking by length" were significant with a 5% confidence interval. The large variance of preference coefficients means that there is heterogeneity of preference among consumers, which supports the validity of the mixed logit model used in this study. In addition, based on the results, we examined the relative importance of calculating the consumer preference ratio to determine whether any attribute level is more favorable or indiscriminate compared to the other attribute levels. The results show that consumers regard price as the most important attribute (the RI of the price attribute is 49.489%). In addition, the behavioral ad-blocking function was the second most

Table 3
Sample alternative set.

Attributes	Service A	Service B	Service C	Service D
Behavioral ad-blocking	Block behavioral ads with high privacy	Block behavioral ads with low privacy	Do not use	Do not use
Repeat ad-blocking	Use	Do not use	Do not use	
Ad-blocking by length	Block ads longer than 5 s	Block ads longer than 10 s	Block ads longer than 15 s	
Ad-blocking by location	Block "before" ads	Block "before," "middle," and "after" ads	Block "before" ads	
Ad-blocking by skippability	Block skippable ads	Block skippable ads	Block non-skippable ads	
Monthly fee (1000 KRW)	6	2	4	
Choose one	A___ B___ C___ D___			

Table 4
Estimation results.

Attribute	Coeff (SE)	SD (SE)	MWTP (KRW)	RI (%)
Block behavioral ads with high privacy	1.038* (0.140)	0.614* (0.242)	1136.321	9.034
Block behavioral ads with low privacy	0.766* (0.175)	1.136* (0.257)	841.842	6.931
Block all behavioral ads	1.307* (0.136)	0.080 (0.353)	1432.151	11.386
Repeat ad-blocking	0.337* (0.130)	1.322* (0.182)	352.106	5.066
Ad-blocking by length	−0.028* (0.014)	0.060 (0.040)	−29.907	2.751
Ad-blocking by location	0.151* (0.060)	0.590* (0.093)	171.205	7.499
Block skippable ads	0.328* (0.132)	0.483* (0.271)	362.595	2.983
Block non-skippable ads	0.519* (0.138)	0.930* (0.221)	548.203	4.860
Monthly fee	−0.899* (0.066)	0.752* (0.067)	–	49.489
# of observations	8000			
Log likelihood	−1963.48			

Note 1: * means significant at the 5% level.
Note 2: Coeff (Coefficient), SE (Standard error), SD (Standard deviation).

important attribute, meaning that consumers tended to dislike their own information being used in advertisements. The relative importance of ad length was the lowest at 2.751%, perhaps due to the large number of skippable advertisements. In the survey, only 78 respondents (15.6%) answered the question “Do you watch the advertisement until the end?” with “I watch to the end.” On the other hand, 422 respondents (84.4%) answered “I don’t watch the advertisement until the end,” and we found that many people avoided advertisements in the middle.

In Table 4, MWTP is an economic measure of how much consumer utility increases or decreases when the level of each attribute changes, indicating if the consumer is willing to pay additional costs. Consumers were willing to pay about 1432 Korean Won (KRW) per month to block all behavioral advertisements; to block advertisements that could not be skipped, they were willing to pay an additional 548 KRW per month. In the case of blocking functions that operate according to advertisement length, as the length of an advertisement increases by 1 s, the payment by consumers decreases by about 30 KRW. That is, consumers are willing to pay about 30 KRW more as advertisement length is shortened by 1 s.

5.2. Market simulation analysis of ad-blocking services

Online video platforms have their own advertising policies, such as changing ad-length, adding ad-locations, and adding new advertising functions (Mei et al., 2007; Pashkevich et al., 2012; Pikas and Sorrentino, 2014). As the consumer’s inconvenience due to online video advertising increases and the importance of online video advertising increases, the advertising policy of the online video platforms becomes more important. Therefore, based on estimations of consumer preference, we forecast the market share of each platform by changing the advertising attributes of each platform. First, we made the assumptions shown in Table 5 for our market share analysis. The base scenario is that there is no function to block the physical characteristics of video advertising. Platform *A* provides free content with 5-second advertisements, platform *B* provides free content with 15-second advertisements, and platform *C* provides paid content without advertisements. Platforms *A* and *B* are modeled under the assumption that there is no behavioral ad-blocking function, repeat ad-blocking function, ad-blocking by length, ad-blocking by location, or ad-blocking by skippability. Except advertising, we also assumed that the content and service functions provided by each platform are the same. The criteria used to divide platform *A* and platform *B* are based on *YouTube*’s advertising policies and the results of existing research. Currently, *YouTube* provides various advertising policies that take into consideration the utility of the creators, content providers, and consumers. *TrueView*, in-stream advertisements on *YouTube* allow consumers to skip ads after 5 s, and the advertiser pays only if the consumer watches for 5 s or longer. Non-skippable video advertisements on *YouTube* require viewing of all advertisements and are 15 or 20 s long depending on the geographical area. When the advertisement length is increased, it is possible to compare how the inconvenience experienced by individual consumers differs. Since such analysis is possible in 1 s units, the representative advertisement length was used for the scenario analysis. Forecasts of future market share is based on Eq. (6) at Section 3. The calculated choice probability refers to the average choice probability of consumer *i* over alternative *j*, and the results can be interpreted as the market

Table 5
Market scenarios of online video platforms.

Scenarios	Market situations
Base scenario	The status of advertisements for each platform is - [Platform *A*] Free content for 15 s advertising - [Platform *B*] Free content for 5 s advertising - [Platform *C*] Paid content without advertising
Scenario 1	In a situation where platforms *A* and *B* both exist in the market, platform *C* enters and changes prices
Scenario 2	In a situation where platforms *A*, *B*, and *C* exist in the market, platform *A* introduces paid behavioral ad-blocking service and changes prices
Scenario 3	In a situation where platforms *A*, *B*, and *C* exist in the market, platform *A* introduces paid all ad-blocking service and changes prices

Table 6
Description of the simulation conditions.

Attribute Platform	Scenario1			Scenario2			Scenario3			References
	A	B	C	A	B	C	A	B	C	
Block behavioral ads with high privacy	0	0	1	0	0	1	1	0	1	Assumption
Block behavioral ads with low privacy	0	0	1	0	0	1	1	0	1	Assumption
Block all behavioral ads	0	0	1	0	0	1	1	0	1	Assumption
Repeat ad-blocking	0	0	1	0	0	1	1	0	1	Assumption
Ad-blocking by length	15	5	0	15	5	0	0	5	0	Google Ads*
Ad-blocking by location	0	0	1	0	0	1	1	0	1	Google Ads*
Block skippable ads	0	0	1	0	0	1	1	0	1	Google Ads*
Block non-skippable ads	0	0	1	0	0	1	1	0	1	Google Ads*
Monthly fee (1000 KRW)	0	0	1–7	1–7	0	7.9	0–7	0	9.7	YouTube Premium*, Netflix*

*Google Ads policy (https://ads.google.com/intl/en/home/), YouTube Premium (https://www.youtube.com/premium/), Netflix (https://www.netflix.com/kr/).

share of each alternative in the scenario situation. To calculate the estimated market share based on choice probability, each reference scenario was selected as shown in Table 6, considering the current market situation.

In scenario 1, we examined how market share changes when platform *C*, which offers paid content without advertisements (or ad-blocking services), enters a market in which there is only platform *A* and platform *B* and changes prices. As a result, before the price is greater than 5000 KRW as shown in Fig. 1, platform *C* occupies about 40–100% of the market, but platform *B,* which provides free content with 5-second advertisements, climbs to No. 1 and claims more than 40% of the market share when prices increase to 5000 KRW, and platform *A,* which provides free content with 15-second advertisements then follows. If we assume that platform companies provide the same content and that advertisements on platform *A* are 10 s longer than those on platform *B*, platform *B*'s market share may be 14% higher than that of platform *A*. We also found that platform *C* services that block all advertisements are not a serious threat to the market shares of platform *A* or *B*.

As in Table 4, the results of this study show that consumers are sensitive to use of their own personal information. In Scenario 2, we examine changes in market share when platform *A* changes prices while providing paid behavioral ad-blocking. Platform *C* provides paid content without advertisements. Therefore, platform C assumes the cost of the service, considering of paid services of 7900 KRW per month on *YouTube Premium* in Korea. As shown in Fig. 2, when platform *A* provides behavioral ad-blocking services for 1000 KRW, it obtains a market share of 86.5%, and when the price is raised to about 3000 KRW, the market share of platform *A* is

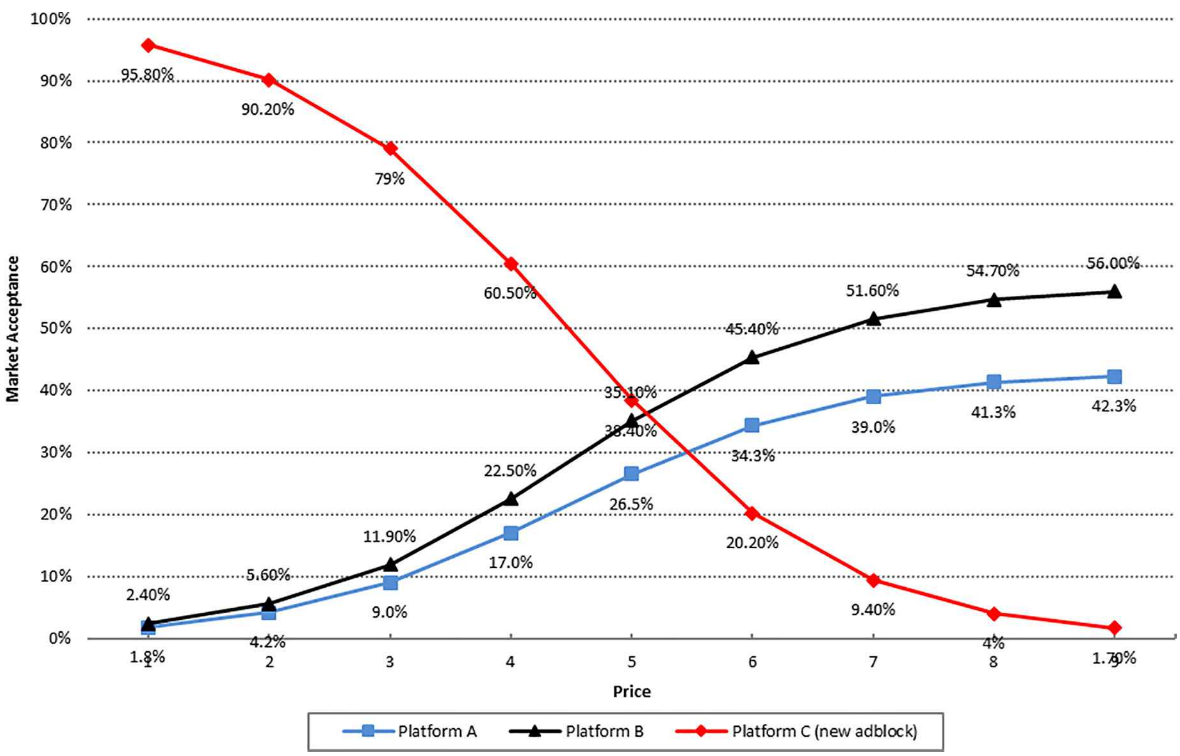

Fig. 1. Market share when platform C changes prices (Scenario 1).

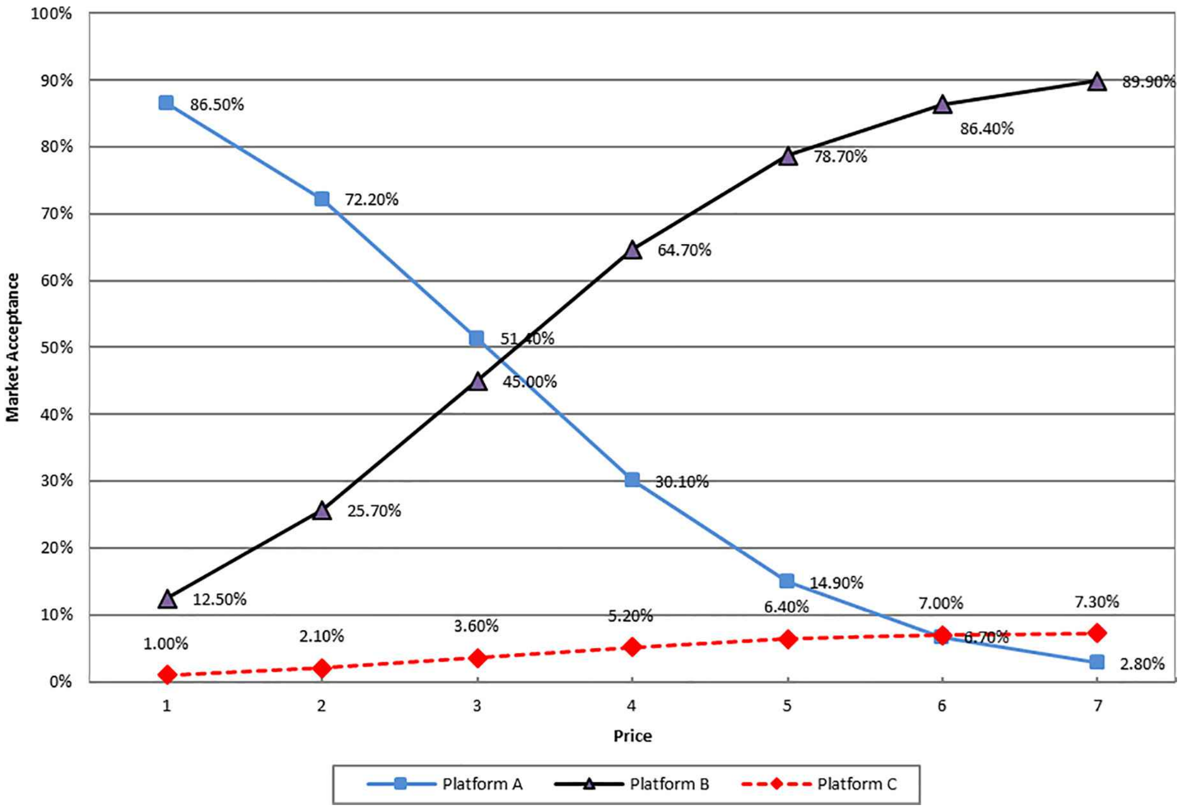

Fig. 2. Market share when platform A introduces paid behavioral ad-blocking services and changes prices (Scenario 2).

overtaken by that of platform *B*.

Finally, in Scenario 3, platform *A* provides free content with 15-second advertisements and introduces a paid service that blocks all advertisements. We assumed that the price of platform *C,* which offers paid content without advertisements, is fixed at 9700 KRW per month using *Netflix* domestic paid service as an example. As shown in Fig. 3, we found that platform *A* occupies about 99% of market share when providing free online ad-blocking and holds the same market share as platform *B* (which provides free content with 5-second advertisements) from a price of about 5000 KRW. Based on these results, if platform *A* provides a paid service that blocks all advertising, it can achieve market share of 50% or more even if the price is raised to 5000 KRW.

These results suggest that paid service without advertisements are attractive to consumers, but that the price attribute is the most important variable determining market share. In a comparison of market share for all ad-blocking services, the optimum estimated price is about 5000 KRW, and more expensive services are not attractive to consumers. In other words, even if ad-blocking services are convenient and effective, high price will deter users. Therefore, online video companies that want to introduce paid ad-blocking services should ensure appropriate pricing.

6. Discussion and concluding remarks

This study was inspired by the increasing number of consumers using online ad-blocking programs. In addition, we noted that consumers who use Internet content for free also positively view paid services such as ad-blocking. Ad-blocking is a phenomenon of advertisement avoidance that has become more actively applied since the development of the Internet, and specifically online video advertising. The fact that consumers want to block advertisements means that they experience inconvenience when watching advertisements, and that Internet platform companies need to understand and reflect consumer experiences about advertising. In addition, based on analyses of consumer preference, we were able to predict changes in market share when companies changed their advertising policies. This suggests that market share prediction is an important criterion in the platform market, where customers are free to switch platforms and companies are free to enter and exit. The online video platform was selected as the target of this research because it is suitable for measuring the inconvenience of advertisements. They cannot be easily avoided, and consumers have to watch advertisements for a minimum length of time before consuming specific content. Consumers responded most sensitively to online behavioral advertising using their own information, while inconvenience had the lowest association with advertisement length. In the case of advertising through traditional media, the act of avoiding or blocking an advertisement is performed to cope with cognitive avoidance, through mechanical avoidance (switching the channel, etc.), physical avoidance (leaving the room, etc.) in a limited manner. For online advertisements, consumers are more positively and directly able to solve inconvenience problems

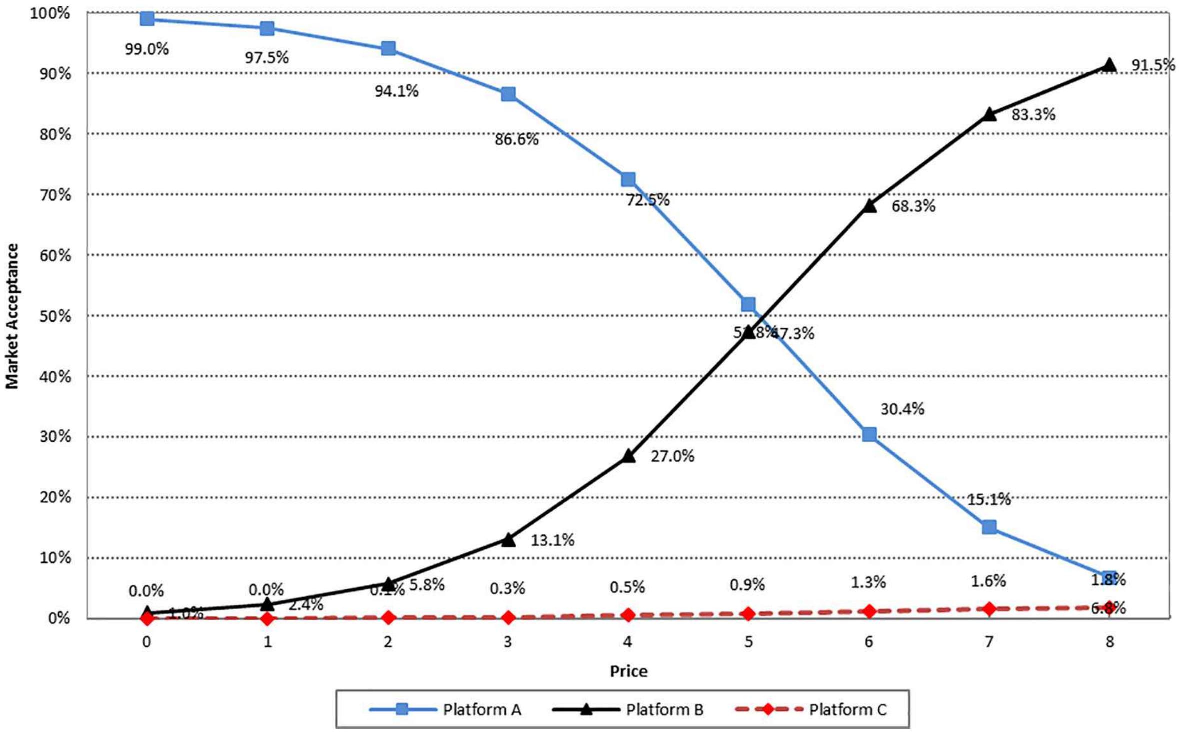

Fig. 3. Market share when platform A introduces paid all ad-blocking services and changes prices (Scenario 3).

associated with variables like the length of advertisements by mechanical avoidance (skipping ads, turning off ads, and using ad-blocking programs) (Speck and Elliott, 1997).

We compared online video advertisements provided by OTT platforms because other Internet platforms like portals, search engines, etc. have much different policies even if they have similar Internet infrastructures. For example, when an advertisement must be watched before consuming video content, the length of the advertisement differs across platforms. In addition, company policies also vary for intermediate advertisements inserted in the middle of content and for post advertisements inserted after content. There are also differences in whether an advertisement must be watched for a certain period of time or whether similar advertisements are repeated, or whether advertisements use personal information. However, all of these conditions can be combined in a variety of ways, and content providers can choose whether to provide advertisements or not. Therefore, in this study we made assumptions about basic functions.

In an analysis of market share between platforms, we differentiated conditions according to the characteristics of advertisements, which constitute the main revenues earned by platform companies. Online video platforms that are competing in the market try to improve the satisfaction of consumers and content providers by changing their advertising policies. For example, in the case of *YouTube*, it is possible to quickly obtain profit by eliminating the skip button, or introducing intermediate advertisements and post advertisements. On the other hand, by providing a short video advertisement (bumper advertisement) of less than 6 s, the user is prompted to recognize the advertisement quickly and to reduce the inconvenience experienced. In addition, *Netflix* has attempted to introduce intermediate advertisements, and is constantly changing and innovating its advertising policies. Therefore, we were able to analyze how the market shares of online video platforms may change due to changes in advertisement policies, and how the market shares of existing platforms may change when a platform with a different advertising policy enters the existing online video platform market.

The limitations of this study include the fact that we focused on advertising to understand consumer inconvenience, and did not examine differences based on the platform and content. In addition, our survey was conducted among only Korean domestic consumers. Therefore, there are limitations in generalizing our findings to global OTT platforms, such as *Hulu*, *Twitch*, *Vimeo*, and *DailyMotion*, which provide similar services.

There are the academic limitations in examining only six advertising characteristics that are the most influential and issues associated with various online video advertising configurations. New services and features emerging from video platforms and advertisements should be considered in future studies. In addition, we were able to grasp consumer preferences regarding inconvenience caused by online video advertising, but our ability to recognize and address these problems in the platform companies and advertisers' views is limited. In order to maintain a sound advertising ecosystem and to create an environment in which a large number of consumers can participate and utilize content, we need to understand the willingness and effort of advertisers and platform companies to improve their advertising. Platform companies and content providers who provide services will be able to use the results of this research to develop advertising policies and strategies that can address consumer inconvenience.

This study was designed to estimate the inconvenience of consumers viewing online video advertising by conjoint analysis and calculate the value of this inconvenience as an economic unit. We found that consumers consider the most serious problem to be the use of personal information. This problem cannot be solved by simple avoidance, which was the biggest inconvenience associated with behavioral advertisements. Advertisers and platform companies attempt to provide behavioral advertisements that use personal information for more targeted advertising. However, the inconvenience of these advertisements was measured at about 3409 KRW, making them more expensive than other attributes. In addition, consumers place a higher value on blocking non-skippable advertisements, because the consumer desire to avoid advertisements is stronger than the desire to watch them.

The desires of consumers to avoid and block advertisements are natural, but increases in advertising and a combination of various technologies might increase consumer inconvenience beyond the limits that consumers can tolerate. Currently, ad-blocking behavior is attributed primarily to a subset of sensitive consumers. However, if the inconvenience associated with advertising accelerates and ad-blocking behavior spreads, the Internet ecosystem itself, which is based on advertising, will face great difficulties. Advertisers and platform companies should provide appropriate levels of advertising and advertising functions, enable consumers to experience the positive effects of advertising, and establish an environment in which advertising can grow together with profits.

In addition, advertisement-based online video platform companies may experimentally predict how their advertising policies will change and how new market participants will affect market share when they enter the market. During the brief history of online platforms, platform companies have been actively entering and exiting the market. It will be necessary to establish optimal strategies and quick response, and remains important to predict the preferences of consumers and content providers (Farrell and Klemperer, 2007; Shankar and Bayus, 2003; Zhu and Iansiti, 2012).

The Internet is a space in which autonomous growth and development are presupposed. If platform companies are willing to lead the way in improving the advertising experience, the Internet ecosystem will grow robustly and consumers will remain actively engaged. We hope that this study will assist the autonomous efforts of Internet platform companies to improve the advertising environment rather than government regulations.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2020S1A5A8045556 and NRF-2020R1F1A1048202).

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