공학박사 학위논문

Evaluating Display Advertising Factors and Waterfall Bidding Strategy for Revenue Optimization of Mobile Publishers

모바일 매체의 수익 최적화를 위한 디스플레이 광고 요소 및 워터폴 입찰 전략 평가

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Abstract

Evaluating Display Advertising Factors and Waterfall Bidding Strategy for Revenue Optimization of Mobile Publishers

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Advertising revenue has become an important revenue source for mobile publishers, along with in-app purchase. Based on empirical data and academic methodology, this study attempted to solve two key problems that mobile publishers face when trying to maximize advertising revenue.

This study analyzed transaction history data of mobile advertising from AD(x) Inc., a company that provides services to optimize ad revenue for mobile publishers by operating multiple ad networks simultaneously, including Google AdMob and Facebook Audience Network.

The first problem mobile publishers face when trying to gain revenue through advertising is determining the optimal ad position and ad format for the service UX of mobile publishers. To provide guidelines for the first decision, this study analyzed characteristics of mobile advertising, including native ads and rewarded video ads, which have been relatively recently introduced. As a result, in addition to various ad factors defined by previous research through traditional advertising media, three new ad factors were summarized: ad density, disclosure position, and disclosure method. Moreover, the relationships among the three new derived ad factors, ad revenue, and ad effectiveness were analyzed.

First, in relation to ad density, which is the proportion of an advertisement's physical area relative to the full-screen area, the higher the ad density, the higher both the ad revenue and advertising effectiveness. On the other hand, among advertisements with similar ad density, there was a difference in ad revenue and advertising effectiveness according to ad format. Among advertisements with low ad density, native banner ads showed higher ad revenue and advertising effectiveness than banner ads. Among advertisements with high ad density, rewarded video ads showed the highest ad revenue, and interstitial ads showed the highest advertising effectiveness.

As for the second new ad factor, disclosure position, the effectiveness of advertisements displayed at the top of the screen was higher in the PC web environment, but advertisements displayed at the bottom of the screen in the mobile environment were higher in terms of ad revenue and advertising effectiveness.

Lastly, in the analysis of the third new ad factor, disclosure method, advertisements with the same ad format as native ads were classified in three categories, based on their development by mobile publishers: “Separated area,” “List UI,” and “Pop-up.” This study analyzed the relationship between disclosure method, ad revenue, and advertising effectiveness. The results showed that the highest ad revenue and advertising effectiveness were found in the “Pop-up” disclosure method.

The second problem that mobile publishers face after determining ad position and ad format is the optimization of waterfall settings such as the priority and reserve prices of each ad network to maximize ad revenue when mobile advertising is served from multiple ad networks. On the other hand, between ad networks and mobile publishers, there is information asymmetry. Hence, ad networks have

more information, so this study proposed a reserve price strategy for the operation of waterfall bidding among multiple ad networks to maximize ad revenue, even under information asymmetry.

First, a demand curve-based model was designed to explain the loss of ad revenue when a mobile publisher sells its ad inventory at a non-optimized price using waterfall bidding. In addition, sensitivity analysis was conducted to show that the proposed model performs better than the company's existing bidding strategy. Moreover, this model enabled mobile publishers to have better performance with independent correlation, not a positive correlation of ad networks' bid prices. Therefore, mobile publishers can use the key finding that the proposed model is more effective in reducing expected advertising losses under information asymmetry. In addition, it was found that performance improved to a greater extent when ad networks have less bid price similarity.

This study provides guidelines that can be utilized not only in an academic sense but also in a real business environment. Standardized knowledge for small- and medium-sized mobile publishers, in particular, which have a relatively high ad network dependency, is suggested to improve their understanding of ad network usage and to establish optimized advertising operation policies.

Keywords: Digital Marketing, Mobile Publisher, Ad Factors, Waterfall Bidding Strategy, Advertising Revenue Optimization

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Chapter 1. Introduction

With rapid advances in information technology, advertising using digital media, in addition to traditional advertising media such as television (TV), newspapers, radio, and magazines is rapidly evolving and growing (eMarketer, 2012b; IAB and PWC, 2018). Since the release of the iPhone in 2007, the rapid adoption and spread of smartphones has led to a surge in interest in mobile advertising among digital advertising, surpassing the quantity of online advertising in 2016 (IAB, 2017).

Mobile advertising is defined as the sending of messages from advertisers via text, graphics, voice, or video through mobile communication devices such as smartphones, tablets, or wireless internet terminals to obtain expected responses from customers (Lee and Park, 2005). Mobile advertising clearly differs from existing advertising media because it can provide users with the information they want anytime and anywhere, based on data such as personal identification numbers, location, and time and also offers the possibility of real-time interaction (Barnes, 2002; Yuan and Tsao, 2003; Tahtinen, 2005).

Mobile advertising can be generally divided into web display advertising, in-application display advertising, and search advertising (Haghirian and Inoue, 2007). This study addresses in-application display advertising, which is presented within mobile applications (hereinafter "apps").

Mobile advertisements through digital media are presented in various ways, using procedures that are different from those employed in conventional advertisements. For example, in newspaper advertising, purchasing a specified advertisement area at a predetermined cost (guaranteed advertising, guaranteed contract) results in the advertiser's content being printed on the desired date for exposure to users.

By contrast, online and mobile advertising are determined by real-time bids. For example, if a user visits a website or mobile app and requests an advertisement, the request is sent to the advertising network (hereinafter "ad network") within 100 ms or less, and the winning bidder who will present the advertisement is determined through real-time bidding (Perliche et al., 2012). Advertisers have a need for automated bidding programs based on rich data and sophisticated models to win bids and present advertising. Advertising through real-time bidding is sometimes called programmatic advertising because of this feature.

Standardized bidding procedures and advertising formats (hereinafter "ad formats") are required among advertisers, publishers, and other participants for advertisements to be presented through real-time bidding, and these procedures and ad formats are defined and managed by various institutes such as the Interactive Advertising Bureau (IAB).

Many ad formats are used in online and mobile advertising, with the oldest being banner advertising (hereinafter "banner ads") and interstitial advertising (hereinafter "interstitial ads"). Banner ads were first activated when they were posted on the AT&T website in 1994 (Briggs and Hollys, 1997; Rohingtia, Dondu, and Hershberger, 2003;

Robinson, Wysocka, and Hand 2007) and subsequently became the most popular type of online display advertising (Hoffman and Novak, 2000; Mangani, 2004). They were displayed as statc image or animated images and usually sized by pixel unit width and height. Sizes defined at this time soon became formatted. Banner ads used in mobile advertising are most commonly presented in a format of 320×50 or 300×250 pixels.

Interstitial ads were widely used from around 1998 because they maximized profits based on users' wait times: advertisements were displayed on the screen while users waited for downloads to complete. Although defined as 320×480 pixels in mobile advertising, these ads are displayed across the entire screen and have developed from simple images to playable and video forms for the experience of advertised games.

Native advertising (hereinafter "native ads") began to appear relatively recently, in 2011. Mobile publishers can edit components of a native ad such as the application icon, title, and main image; native ads therefore offer features that allow publishers to lay out and deploy components that match the service's graphical user interface (GUI). The native ad format is used by many social networking services such as Facebook and Instagram (See Figure 1), and it has different advantages compared with existing banner ads and interstitial ads. These include minimizing the tendency to avoid advertising by presenting advertisements resembling the service's GUI, so that users recognize them as content rather than as advertising.

Figure 1. Example of a native ad on Facebook

Rewarded video advertising (hereinafter "rewarded video ads") is a format that began to appear around 2016 that offers users compensation, called "rewards," for goods or items in a game when they complete the viewing of video-type advertising. This ad format is seen in mobile games. Unlike banner ads and native ads that are displayed in certain areas in advance, regardless of the user's choice (push type), rewarded video ads are a pull type of video advertising that is displayed only when the user wants compensation.

A mobile publisher receives advertisements from one to as many as five or seven ad networks, depending on the size of his or her user traffic. The most widely known ad networks are Google AdMob, Facebook Audience Network, and Twitter MoPub, which offer large and small ad networks for each country and region.

The waterfall strategy or header bidding is used to manage various ad networks simultaneously. Header bidding is a parallel method whereby advertisement requests are simultaneously transmitted to multiple ad networks, and the most expensive advertisements are sent out after the bidding results are received from each ad network. The waterfall strategy is a serial method whereby an advertisement request is sent sequentially to each ad network. An advertisement request is sent to one ad network, and the advertisement is displayed when the advertisement is served by that ad network; otherwise, it is sent to the next ad network.

In general, the performance of the devices and communications infrastructure where advertising will be presented must be high for header bidding to operate smoothly, because advertisement requests must be sent to multiple ad networks in a very short time and receive responses. Therefore, header bidding is mainly used in high-performance environments involving PCs or servers, for example, and the waterfall strategy is mainly used in relatively low-performance environments such as mobile environments.

Advertising servers and platforms for setting up ad networks and running the waterfall strategy with multiple ad networks are called “mediation” services. Several ad networks, including Google AdMob and Twitter MoPub, also offer mediation platforms. However, even if a publisher uses a mediation platform to facilitate the setup of an ad network, determining the actual setting value, reserve price, and number of impression limits per device (frequency cap) is another matter for the publisher to decide, and advertising revenue may vary significantly depending on this decision.

With the rapid evolution and growth of mobile advertising technologies and market size, advertising revenue has become a major income source for mobile publishers, along with in-application purchases (Liu, 2016). However, two major challenges must be addressed for mobile publishers to maximize advertising revenue (See Figure 2).

1. Determining the advertisement's placement and ad format, considering the service's GUI and user experience (UX)

2. Managing the waterfall strategy by setting values that maximize advertising revenue

In this study, these two issues, which are key to maximizing advertising revenue, are studied through empirical data and academic methodology.

First, an analysis was conducted using data from various mobile apps that maximize advertising revenue through mediation platforms to provide guidelines for selecting advertisement placement and ad formats optimized for the service UX of mobile publishers. Characteristics of each ad format were theoretically analyzed and organized into advertising factors. Then, optimized advertisement factors were proposed for consideration by analyzing the influence of each factor on advertising revenue and effectiveness, based on characteristics of the service UX at the time of the addition of the advertisement to the service's GUI or UX by the mobile publisher.

In addition, once the placement of the advertisement was determined, guidelines and sensitivity analysis of the waterfall strategy for better performance were proposed to maximize advertising revenue. Data of various mobile apps that maximize advertising revenue through mediation platforms were analyzed, and the bidding situation was theoretically organized to maximize the mobile apps' advertising revenue. The advertisement inventory transaction history data were analyzed, and methods of setting the ad network request orders and reserve prices in the waterfall bidding strategy were devised. This study proposes a dynamic reserve pricing strategy that outperforms the historical average-based reserve pricing strategy previously employed by mobile publishers through those procedures.

This study suggests guidelines and academic implications to generate more advertising revenue for numerous mobile publishers that use multiple ad networks in actual management environments. Moreover, it provides standardized knowledge that cannot be gained without inhouse R&D related to advertising for small- and medium-sized publishers, which have a relatively high dependency on ad networks, thereby improving the understanding of advertising factors and networks. This study also suggests methods of establishing advertising operations policies and optimizing monetization levels and service UX for mobile publishers.

This study consists of five independent chapters. Chapter 2 summarizes the existing literature on real-time bidding, ad formats, and advertising revenue and effectiveness indices, which are related to the core concepts of this study. Chapter 3 analyzes the effects of advertising factors and ad formats on advertising revenue and effectiveness. Chapter 4 examines methods of maximizing advertising revenue by optimizing reserve prices in waterfall strategies of ad networks. Based on the analysis and research results in Chapters 3 and 4, the relationship between advertising factors and revenue (or advertising effectiveness) are suggested in Chapter 5, along with guidelines for mobile publishers considering the waterfall strategy to maximize advertising revenue.

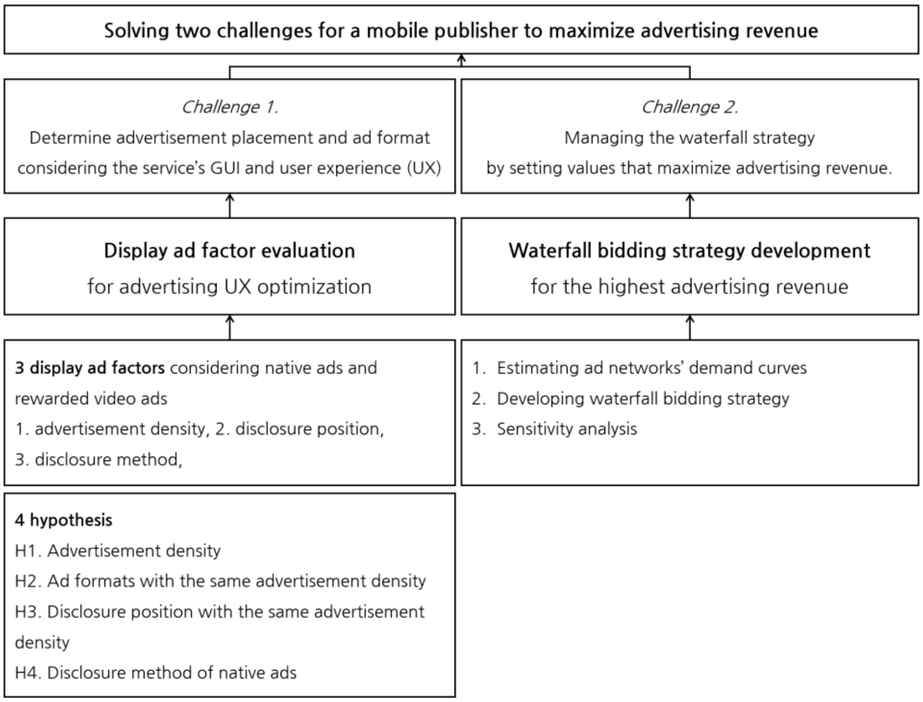


Figure 2. Overview of study framework

Chapter 2. Literature Review

2.1 Real-Time Bidding

Real-time bidding, which emerged in 2009, is one of the most important concepts related to online display advertising introduced in recent years. Prior to the appearance of real-time bidding, the industry was divided among publishers and advertisers, and advertisers directly contracted with publishers in advance (premium contract, guaranteed contract) to display advertisements. Today, it is not possible to define the users targeted by advertising with publishers, and details of conditions such as the amount of exposure cannot be determined in advance. A contract is concluded based solely on the reputation of the publisher (Bock and Poel, 2010; Bilenko and Richardson, 2011; Abramson, 2012). Contracts are mainly based on the cost per mille (CPM) amount, according to the number of impressions, but the publisher itself cannot be certain of the number of impressions; therefore, conservative estimates of anticipated exposure are made by advertisers, instead of contracts, to avoid penalties for under-impressions (Roles and Fridgeirsdottir, 2009; Vee et al., 2010).

This situation led to the creation of ad networks, whereby publishers register advertising inventories, suggest the remaining number of impressions to advertisers. And advertisers register their advertisements on the ad network to display them to publishers. Unlike with premium contracts, the exposure of advertisements through ad networks is not guaranteed for advertisers and publishers. Advertising networks analyze publishers to understood them and their users and to present advertisements to appropriate publishers. Advertising networks collect behavioral information such as user preferences, interests, geographical locations, and local time to distinguish users and attempt to match advertisers with appropriate publishers and their users.

As the number of ad networks increased, advertising exchanges (hereinafter, “ad exchanges”) appeared naturally. Advertisers wished to increase advertising exposure with smaller budgets. Publishers believed that bidding prices would become higher as more ad networks participated. Real-time bidding is the most important feature introduced by ad exchanges, which are a type of marketplace for advertisers and publishers to achieve their goals. Real-time bidding enables the supply of advertisements through auctions for each advertisement request. It also changes the fundamentals of the advertising market from publisher or advertisement placement to user-optimized approach.

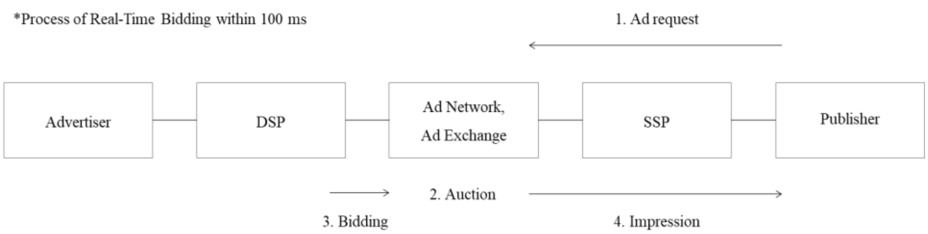


Figure 3. Real-time bidding process

Figure 3 shows the whole process of real-time bidding. When an opportunity to display an advertisement on the media arises, an advertisement request is sent to an ad network or ad exchange, an auction is immediately initiated based on the request, and various advertisers or their agencies (demand-side platform, DSP) bid to participate. The highest or second highest bid is sold, and the successful bidder’s advertising materials are sent to the publisher, resulting in an actual impression. This series of processes is called real-time bidding because it occurs within 100 ms of the advertisement request and includes the advertisement impression.

Several studies have been conducted to reveal the shortcomings of real-time bidding as it developed. Exposure of advertisements through real-time bidding reduces the validity of guaranteed contracts with advertisers because real-time bidding splits advertisement exposure to customers into small pieces of targeted advertisement. Moreover, competition among advertisers for specific publishers or advertisement exposure is dispersed, owing to fine-grained targeting, and the number of bidders for a single advertisement request is reduced. This phenomenon results in lower advertising revenues, from the publisher’s perspective (Levin and Milgrom, 2010; Rafieian and Yoganarasimhan, 2017).

Table 1. Types of programmatic advertising

Transaction type	Media type	Unit price type	Advertiser : Media
Programmatic Guaranteed	Reservation	Fixed price	1:1
Preferred Deals	Bidding		
Private Marketplace		Bid price	N : 1
Open Marketplace			N : N

The features of real-time bidding are reasonable for advertisers, but "fair" bidding may lead to advertisements not being displayed. Therefore, advertisers still present guaranteed or preferred deals to publishers, with additional budgets, to avoid a probable lack of exposure. Table 1 summarizes the different types of programmatic advertising that increase the chances and priority of advertisement exposure between advertisers and publishers.

2.2 Ad format

Ad formats must be defined and standardized to supply advertisements through an ad network or ad exchange, that is, for advertisement requests and transactions to be made through real-time bidding (programmatic advertising). Thus, various organizations and companies have gathered to establish institutes such as IAB and defined policies and standards of ad formats. This section discusses native ads and rewarded video ads which emerged relatively recently and are being used widely.

2.2.1 Native Ads

Native ads, introduced in 2013, accounted for 58.3% of U.S. display advertising spending in 2018, and over 90% of advertising spending of native ads were run on mobile environments (eMarketer, 2018).

Native ads are an ad format that enables the publisher of mobile app developer to design and define the layout of advertisement messages (Wojdynski and Evans, 2015). This ad format resembles the surrounding GUI of contents when displayed within the media, allowing users to perceive it as content, rather than as advertising. It displays the advertisement naturally, which minimizes the user’s tendency to avoid advertising.

Banner ad sizes are 320×50 pixels or 300×250 pixels, and there is a distinction between the advertisement area and service area, while the placement size and layout of necessary elements in a native ad can be designed as intended by the mobile app developer, as long as they include the five necessary elements: a logo or application icon, advertisement title, advertisement mark (“sponsored” or “AD”), “AdOptionsView” icon, and call-to-action button (See Figure 4). Hence, if the layout resembles the mobile app’s service GUI, users are naturally exposed to advertising as if it is content.

Flexibility in advertisement size means that native ads can be displayed where both banner ads and interstitial ads would have been displayed. Native ads can also be displayed between content or as pop-ups. Mobile app developers can present native ads of any size and in any location in their services, as long as they follow the rules of native advertising such as including the five necessary elements.

The flexibility of native ads may represent another challenge for mobile app developers in terms of revenue maximization. If mobile publishers only consider their advantages and use them hastily, without properly understanding their characteristics or elements, the performance of native ads may not be maximized in terms of advertising revenue. Therefore, this study analyzes the influence of native ads on advertising revenue and effectiveness according to changes in various factors and presents guidelines for mobile publishers adding native ads to their mobile services.

1. [Required] Logo or app icon
2. [Required] Ad Title
3. [Required] Ad mark (‘Sponsored’ or ‘AD’)
4. [Required] AdOptionsView icon
5. [Optional] Media view
6. [Optional] Social Text
7. [Optional] Text
8. [Required] Call to Action Button

Figure 4. Ad format policy of native ads (Facebook)

2.2.2 Rewarded Video Ads

Digital video advertising has grown at the fastest pace in recent years, with the mobile video advertising market growing by 29.2% in 2018 in the United States and 22.6% (IAB/PwC, 2018).

Digital video advertising can be largely divided among non-rewarded video ads and rewarded video ads. Non-rewarded video ads include forced exposure just before users watch video-type content services such as YouTube and NAVER TV. Users may be more dissatisfied if they are forced to watch entire advertisements because video ads are usually 15–30 seconds-long. In most cases, the “skip” button is displayed after five seconds of viewing to allow users to decide whether they wish to watch non-rewarded video ads. However, advertisements that force users to watch for six seconds are tested, instead of the “skip” button in YouTube. Non-rewarded video ads have characteristics like banner ads and interstitial ads, which are provided as part of the push strategy.

Rewarded video ads are an ad format that provides users with rewards such as mobile game items in return for watching video ads. When compensation for users such as goods and items can be provided within services such as mobile games, designing the UX for advertising is easy. Therefore, rewarded video ads are popular in mobile games for various advertising purposes such as user retention and premium services trials, but there is a strict policy of not allowing cash-equivalent rewards that limits the use of rewarded video ads in most ad networks.

Rewarded video ads are part of an advertising pull strategy because they are displayed when the user is willing or chooses to receive compensation. The natural insertion of advertising material into mobile app service GUIs is also simplified by the fact that only the compensation and trigger buttons such as “view advertising” are required to be displayed before the video ads are played. When video advertisements begin to play, they are displayed in full-screen size. Users are forced to watch them and cannot escape the screen during playback. The frequency of advertisement exposure per device is usually limited because many users are only seeking compensation.

Rewarded video ads have long existed, and their UX is completely different from push-type ads such as banner ads and interstitial ads. Therefore, there is a definite need for guidelines for mobile publishers.

2.3 Advertisement Performance Index

The click-through rate (CTR), or ratio of clicks to impressions (exposure) in advertising (Schonberg et al., 2000), is one of the oldest ways of evaluating online advertising effectiveness. Clicks are considered to be the most direct, immediate user responses with user actions that can be easily and clearly observed (Chatterjee et al., 2003; Lawrence, 2000; Singh and Dalal, 1999).

Advertisers' goals are to increase awareness, promote positive attitudes, increase participation, increase conversion rates, and promote re-purchase by displaying advertisements. Various metrics have been proposed to measure these goals. Examples include 1) page view, 2) advertisement impression, 3) click count, 4) visitor count, 5) unique visitor count, 6) path analysis, and 7) conversion rate in the web environment (Rosenkrans and Ginger, 2007).

Two of the most widely used measurement values are CPM and CTR (Hagen et al., 2006; Punyatoya, 2011; Rosenkrans, 2007). CPM is the cost of 1,000 impressions and has generally been used in traditional media such as TV and newspapers. Advertisements that use CPM on a billing basis charge advertiser regardless of their advertising effectiveness. This method is most advantageous when charging mobile app developers.

Models charge advertisers according to user behavior or performance such as clicking, installing mobile apps, and purchasing products. Depending on the advertiser's goals, the charging mechanisms are divided among cost per click (CPC), cost per action (CPA), and cost per sale (CPS). The CPC model, which only charges a fee when a click occurs is the most widely used. The market size of such performance-based advertising models exceeded that of CPM billing advertisements in 2006 and is increasing (Lin, Ke, and Whinston, 2012). For publishers, CPM is the most advantageous method of billing advertisements.

The emergence of various advertising billing models such as CPM, CPC, CPA, and CPS has resulted in difficulties determining whether costs paid by advertisers are high or low, and mobile app developers have had challenges determining which model to select. Estimated cost per mille (eCPM), a standardized measure of advertising revenue earned divided by number of impressions (See Table 2), was developed to solve this problem and enables advertisers to set and compare bids for advertisements based on the desired number of impressions. Moreover, it facilitates the task of mobile app developers in evaluating the value of advertisements, whatever the billing model they apply to their inventories.

In this study, eCPM is used as an indicator of both advertising revenue, to analyze the influence of various advertising factors on advertising revenue, and as a parameter of reserve price, to optimize the operation of ad networks. In addition, CTR, an index that measures user behavior or reactions, is employed directly to examine the influence of advertising factors on effectiveness.

Table 2. Index to measure advertising performance

Index	Definition	Formula	Description
CTR	Number of clicks divided by number of impressions	$CTR = \frac{click}{Impression}$	Direct and immediate behavioral user response to advertising
eCPM	Revenue divided by number of impressions multiplied by 1,000 (mille) regardless of billing type	$eCPM = \frac{Revenue}{Impression}$	A standardized measure of ad revenue earned as a result divided by the number of impressions.

Chapter 3. Evaluation of Ad Factor

3.1 Introduction

An ad format consists of various visual or environmental elements. A single advertisement impression affects a user's thoughts or behaviors because various advertising factors are applied. Therefore, examining the relationship between ad format and effectiveness is the same as studying the relationship between advertising factors and effectiveness.

Existing studies categorize advertising factors and analyze the influence of each factor on advertising effectiveness. The research also presents a framework of the relationship between different advertising components and effectiveness by properly grouping various factors.

First, the framework that describes the relationship between advertising factors and effectiveness is the Interactive Advertising Model (IAM) proposed by Rodgers and Thorson (2000). In this model, advertising factors that affect effectiveness are divided into two groups controlled by advertisers and consumers. Online Behavior Advertising (OBA), proposed by Boerman and colleagues (2017), was designed based on advertising factors classified into groups controlled by advertisers and consumers such as IAM but extended according to the perspective of user targeting, compared with those previously included. The Mobile Advertising Effectiveness Framework proposed by Grewal and colleagues (2016) defines several advertising factors based on the goals and objectives of advertisers and proposes a macro perspective by adding context and market- and business-related factors. In addition to advertisers and users, the Integrated Mobile In-App Effectiveness Framework proposed by Truong and colleagues (2019) expands previous models by adding advertising factors that are controlled by ad networks and mobile publishers (See Figure 5).

With the rapid development of advertising technology, the framework to describe the relationship between advertising factors and effectiveness is also rapidly evolving and being updated. Therefore, this study focuses more on advertising factors than the framework itself to examine their influence on effectiveness or revenue. Park and colleagues (2008) compiled 50 advertising-related studies and divided them into three main categories: advertisement factors, environmental factors, and audience factors. Advertisement factors concern characteristics that constitute advertising such as design and content. Environmental factors include the context and repetition of display advertising. Finally, audience factors relate to the user's attitude, experience, and involvement.

Based on Park and colleagues' classification, the analysis of native ads and rewarded video ads, which were recently introduced, reveals additional factors, namely: 1) disclosure position, 2) disclosure method, and 3) advertisement density. These are not explained by previously defined advertising factors.

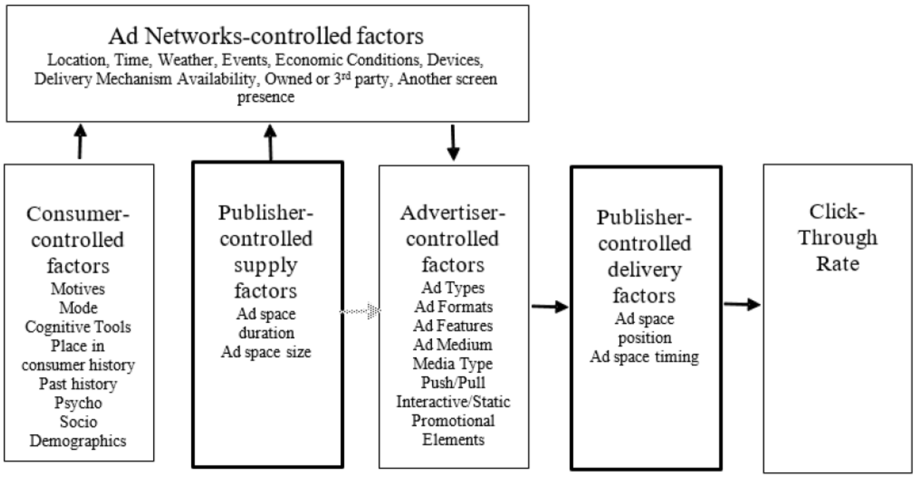


Figure 5. Integrated Mobile In-App Effectiveness Framework (Truong, 2019)

Disclosure method is classified as an advertisement factor. Disclosure position and advertisement density, an index indicating the ratio of advertisement area size to mobile screen size, are classified as environment factors. The definition and characteristics of these new factors are summarized in Table 3.

Table 3. Ad factors defined by Park et al. (2008) and new ad factors (orange color)

Category	Factors (Park et al., 2008)	Modified Factors
Advertisement factors	Design	Design
	Content	Content
		Disclosure Method
Environmental factors	Context	Context
	Exposure time, Repetition	Exposure time, Repetition
		Disclosure Position
		Ad Density
Audience factors	Experience, Attitude	Experience, Attitude
	Involvement	Involvement

3.1.1 Advertisement Factors

Design. Design factors, including advertisement placement size, color, music/sound, animation, and length (time) are related to methods of designing for advertising to increase its effectiveness.

Many studies have analyzed the relationship between size and advertising effectiveness. Research results have shown that the larger the advertisement placement, the greater the effectiveness, regardless of the type of advertising medium (Hendon, 1973; Cho, 1999; Baltas, 2003; Chandon et al., 2003). In an empirical study, Li and colleagues (2003) found that CTR does not increase in proportion to the size of advertisements. Dreze and Hussherr (2003) argued that a small banner has the same advertising effectiveness as a large one. The results of previous research on the size of advertisements are more meaningful for devices with displays that are smaller than 1/10 of the PC environment such as smartphones and smart watches, but additional research is needed.

Another study analyzed the influence of animation on advertising effectiveness. User response was analyzed by displaying three types of advertising, including animation, images, and text to Internet shoppers. The results showed that advertising with animation had a positive effect on users' memory and recognition, including by attracting user attention and encouraging a positive attitude toward advertising (Ku et al., 1997).

Advertisement length has been much studied in relation to TV advertising, in which it is an important factor directly related to cost. Moreover, the length of advertising has become an important factor as rewarded video ads have grown significantly with the development of telecommunications infrastructure. This is explained as follows: the longer the length of the advertisement, the more repeatable the information conveyed (Fabian, 1986; Patzer, 1991). A 15-second advertisement is no more effective than a 30-second one at delivering information, generating interest, and delivering reliability in advertising (Mord and Gibson, 1985). However, we can infer from YouTube's recent six-second video ads that shorter video ads are emerging, although the length of advertising influences effectiveness.

Content. Unlike design factors that are related to size, multimedia function, and advertising length, content is related to storyline and method of expression.

In the past, when TV and radio commercials were mainstream, advertising content such as buzzwords and popular songs were important enough to account for most of advertising's effectiveness.

However, in current modern programmatic advertising, content customization for each individual user is becoming more important. A few years ago, digital advertising used artificial intelligence to automate content design. For example, if a dating mobile app was advertised, the advertised images of the female models were automatically optimized based on the country or region; hair color, eye color, and skin color were similarly adjusted to appearances in the region, inducing certain behavior by users exposed to the advertisement.

Disclosure Method. Native ads can be similarly displayed in or around the service GUI, unlike banner ads, which are displayed in a separate area to the service area because mobile publishers can display an advertisement in the desired layout within predetermined guidelines.

List UI is the most common example of the use of native ads. List UI is a structure in which small units are repeatedly arranged, allowing advertisements to be placed between them. In addition, a native ad can be displayed in a pop-up UX, where the service GUI is the lower layer, and the advertisement is configured in the form of a pop-up or interstitial ad on the upper layer. Moreover, native ads with flexible layouts provide various new UXs, according to mobile publishers' designs.

This study compares the advertising revenue and effectiveness of the three disclosure methods most commonly experienced by users: 1. "Separated area," "List UI," and "Pop-up" (See Figure 6). Then, guidelines for mobile publishers concerning how to display native ads are proposed.

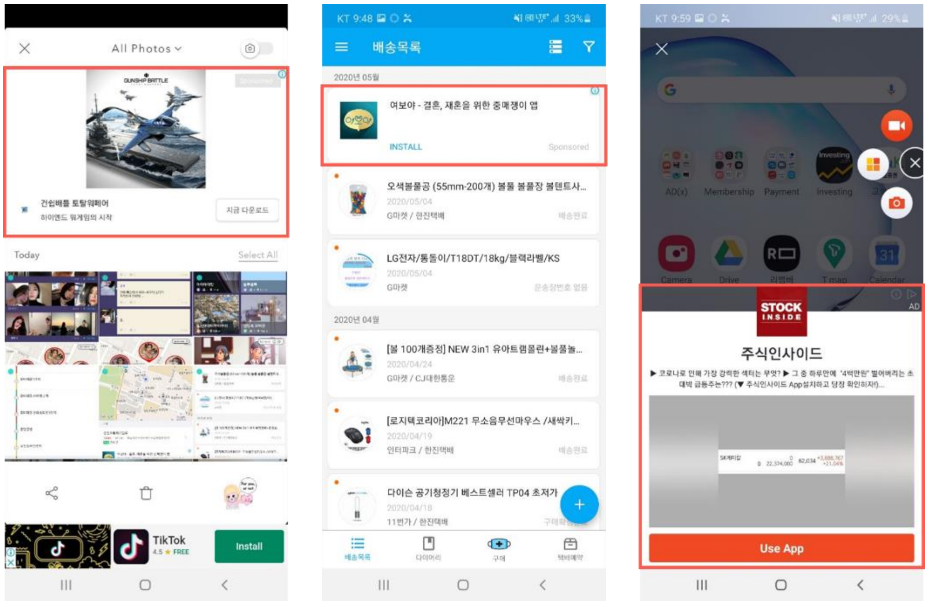


Figure 6. Three types of disclosure method; “Separated area”, “List UI” and “Pop-up”

3.1.2 Environmental Factors

Context. The advertising situation and context are important environmental factors. Banner ads displayed on a website are most affected by the complexity of the surrounding content (Danaher and Mullarkey, 2003).

In a mobile environment, the concept of context must be expanded. The information contained in the advertisement and factors such as location and time should be considered together. Four elements of technical context, user, physical context, and time were proposed to define the concept of context (Chen and Kotz, 2000; Hristova and O’Hare, 2004). Technical context refers to surrounding technical resources such as network connectivity and bandwidth. User includes the user's profile and social status. Physical context refers to the physical environment such as light, noise, and temperature. Time means day, week, and season.

Exposure Time and Repetition. Previous studies have concluded that the longer an advertisement is displayed, the faster a user remembers. In a web environment, the longer the exposure duration of banner ads to web pages, the more positive the effect on the user's memory and cognition (Mayer and Moreno, 2002; Danaher and Mullarkey, 2003).

When advertising is repeatedly displayed, it positively influences the user's memory. However, as the number of iterations increases, users begin to learn and become bored; thus, its effectiveness is reduced. In traditional media, repetition of advertising and user attitudes have an inverted U-shape relationship (Cacioppo and Petty, 1979). As the advertising repeats, recall of the advertisement increases; frequent repetition, however, leads to dissatisfaction, annoyance, and memory loss (Alwitt and Mitchell, 1985; Appel, 1971; Cacioppo and Petty, 1979; Gorn and Goldberg, 1980; Grass and Wallace, 1969). This finding is the same for TV and Internet environments (Park et al., 2008).

Disclosure Position. The disclosure position, where advertisements are displayed, is an important factor of advertising effectiveness. Faraday (2000) proposed two successive steps whereby the user navigates information based on a visual hierarchy model. The user first finds an entry point on the screen and searches nearby to obtain information. This entry point depends on pre-existing expectations, based on the user's experience (Roth et al., 2010), and various patterns can occur depending on the location of the area where the content exists.

Several studies related to online reading behavior have shown that information in the upper left corner is most easily noticed (Nielsen, 2006; Shrestha and Lenz, 2007). Users look at the top left first, then search for information in a horizontal direction to the right, then in an "F" shape in the downward direction.

However, the user expects advertising to be located at the top or right side of the screen (Shaikh and Lanz, 2006), and banner ads displayed at the top of the screen tend to be ignored, even though the user may be interested in such information. This phenomenon is called "banner blindness" (Benway, 1998). Another study also showed that users perceive advertisements more easily when they are placed above or below content (Boerman et al., 2014).

Prior to the introduction of native ads, banner ads were most commonly seen at the top or bottom of the screen or content, but native ads can be displayed in various locations. This study analyzes the influence on advertising revenue or effectiveness of disclosure positions in a mobile environment and proposes guidelines based on them.

Advertisement Density. The concept of advertisement density proposed by Yuan (2015) is defined as the proportion of advertising displayed on the screen compared to the web page size. Users were distracted by advertisements displayed on web pages, which resulted in dissatisfaction (Rohrer and Boyd, 2004) and led to the development of the concept of advertisement density to analyze and determine the optimal proportion of advertisements on a web page. The analysis results showed that the greater the competition for advertising, the higher the advertisement density; a negative correlation exists between advertising revenue and advertisement density. Moreover, advertisement density has increased with the increase in daily page views over the past few years.

In a mobile environment, the size of display devices is smaller than that of a PC by about 1/10 to 1/20. When considering the relative proportion of advertisements in the mobile environment, it is important to note that users may recognize larger advertisements and tend to reject them more. Therefore, it may also be important to analyze advertising revenue and effectiveness based on density in the mobile environment.

This study analyzes the influence of mobile advertising density on advertising revenue and effectiveness and presents conclusions concerning what is helpful for mobile publishers adding advertisements.

3.1.3 Audience Factors

Experience and Attitude. . Users' attitudes toward advertising are formed based on their experiences. Attitudes can be strengthened or weakened over a long period of time and can be classified as attitudes toward brands, media, and advertising itself. Attitudes toward advertising are often negative, even if advertising itself is helpful to users. Entertainment, reliability, and information positively influence attitudes toward advertising, and stimuli are known to have a negative influence

(Tsang et al., 2004). Attitudes toward media also affect advertising effectiveness. Different media can result in completely different communications, even if the same advertisement is presented to the same user (Assmus, 1978).

Based on the web advertising model, Ducoffe (1996) analyzed the effects of informativeness, entertainment, and irritation on user attitudes toward mobile advertising and revealed that entertainment and informativeness significantly influence user attitudes. In mobile environments, users can experience entertainment such as video and manipulative interactive content as well as static images (Oulasvirta et al., 2012).

Involvement. Involvement refers to the degree of interest and connection between users and stimuli such as advertisements. Depending on their degree of involvement, users have very different ways of processing the information they receive through advertising (Krugman et al., 1995). Users try to acquire more information from advertising about high-involvement products.

Directly measuring the degree of involvement is difficult; therefore, there have been attempts to calculate it using other relevant variables. Zaichokowski (1985) developed an index called the Personal Involvement Inventory and categorized degrees of involvement as personal, physical, or situational, while creating new indicators to measure involvement.

3.2 Hypotheses and Dataset

In this study, among the various factors discussed above, the analysis focused on advertisement density, disclosure position, and disclosure method, because mobile publishers can control these three advertising factors of choice in a programmatic advertising environment. Advertisement factors of design, content, exposure time, and repetition are determined by advertisers or DSPs. Advertising factors of context, experiences, attitude, and involvement are highly dependent on the audience.

3.2.1 Advertisement Density

From the perspective of mobile publishers, the order of advertising factors to be analyzed is decided by imagining the process of adding advertisements to their mobile apps. The first advertising factors to be considered are advertisement density (the ratio or percentage of advertisement placements the mobile publisher will position on a screen) and ad format. Based on previous studies on advertisement size, which is similar to advertisement density, conclusions on advertising effectiveness are controversial. Several researchers have shown that the larger the advertisement placement, the more effective the advertising, regardless of the advertising media type (Hendon, 1973; Cho, 1999; Baltas, 2003; Chandon et al., 2003). However, Li and colleagues (2002) showed in an empirical study that CTR does not increase in proportion to advertisement size. Dreze and Hussherr (2003) argued that a small banner ad has the same advertising effectiveness as a large one.

However, the user's sensitivity to advertisement size or density is influenced by the size of the display device, which is much smaller in the mobile environment than in that of the PC. Therefore, the effect of increased advertisement density on advertising and advertising revenue must be analyzed.

Hypothesis 1.a.

As advertisement density increases, advertising revenue (eCPM) increases.

Hypothesis 1.b.

As advertisement density increases, advertising effectiveness (CTR) increases.

3.2.2 Ad format with the Same Advertisement Density

Native ads can be displayed as they were designed by the mobile publisher. Therefore, native ads can be designed as advertisement placements with a size similar to banner ads, or of interstitial ads. This study examines whether the same advertising revenues and effectiveness occur between different ad formats with the same UX characteristics such as advertisement size and density.

Hypothesis 2.a.

Advertising revenue (eCPM) and effectiveness (CTR) will be similar between banner ads and native banner ads with similar advertisement density.

Hypothesis 2.b.

Advertising revenue (eCPM) and effectiveness (CTR) will be similar between interstitial ads, native interstitial ads, and rewarded video ads with the same density.

3.2.3 Disclosure Position with the Same Advertisement Density

Disclosure position is also an important factor of advertising revenue and effectiveness. On the one hand, several studies related to online reading behavior have shown that the information in the upper left corner is most easily noticed (Nielsen, 2006; Shrestha and Lenz, 2007). On the other hand, the user expects that the advertisement will be placed on the top or right side of the screen (Shaikh and Lanz, 2006) and tends to ignore banner ads displayed at the top of the screen (Benway, 1998).

Therefore, this study examines the influence on advertising revenue or effectiveness according to disclosure position with a similar density.

Hypothesis 3a.

A disclosure position at the top of the screen has a positive influence on advertising revenue (eCPM).

Hypothesis 3b.

A disclosure position at the top of the screen has a positive influence on advertising effectiveness (CTR).

3.2.4 Disclosure Method of Native Ads

Disclosure method has also diversified with the introduction of native ads. Disclosure method is slightly different from advertisement size and disclosure position of advertisements discussed in previous studies.

A banner ad is provided in such a way as to separate the mobile publisher's service area and advertisement area by displaying the advertisement on a specific area of the screen, that is, a "Separated area." In addition, many mobile developers select a form that naturally displays both services and contents ("List UI") or displays information on an upper layer ("Pop-up").

This study analyzes how advertising revenue or effectiveness vary depending on disclosure method using native ads that can be developed and displayed through various disclosure methods of

"Separated area," "List UI," and "Pop-up."

Hypothesis 4.a.

"Pop-up" has the highest advertising revenue (eCPM) among "Separated area," "List UI," and "Pop-up."

Hypothesis 4.b.

"Pop-up" has the highest advertising effectiveness (CTR) among "Separated area," "List UI," and "Pop-up."

3.2.5 Dataset

Daily advertising performance data were collected from 17 different mobile apps from January 2019 to December 2019. Table 4 presents the descriptive statistics of our dataset, and Table 5 show the description of variables. Except for AdDensity, CTR and eCPM have large skewness, implying that both variables do not follow normality. When the absolute value of skewness is larger than 1, the variable does not follow normality (Keene, 1995). The analysis was conducted through log transformation of CTR and eCPM variables to reduce the large skewness of variables.

Table 4. Descriptive statistics of dataset

	CTR	eCPM	AdDensity
Obs.	16,817	16,817	16,817
Mean	1.354	2.091	0.430
Std. Dev.	2.323	19.459	0.401
Skewness	9.012	89.773	0.642
Kurtosis	254.662	8480.751	1.553
Min	0	0	0.058
Max	100	1988.220	1.000

Table 5. Description of variables

Variable		Definition
CTR		Number of clicks divided by number of impressions
eCPM		Revenue (cost for advertisers) divided by number of impressions multiplied by 1,000 (mille) regardless of billing type
AdDensity		Percentage of advertising area on a screen
Ad Format	*BannerAd*	Ad format with a rectangular shape, generally 320x50 px
	NativeAd	Ad format with a free layout including five necessary elements
	NativeBannerAd	Native ads the size of banner ads
	NativeInterstitialAd	Native ads the size of interstitial ads
	InterstitialAd	Ad format displayed across the screen, generally 320x480 px
	RewardedVideoAd	Video ads that reward for watching ads for 15 to 30 seconds
Disclosure Position	*PositionMiddle*	Ads displayed in the center of the screen
	PositionBottom	Ads displayed at the bottom of the screen
Disclosure Method	*List UI*	Ads displayed between small units in the list
	Pop-up	Ads displayed on the upper layer covering the service UI

3.3 Results

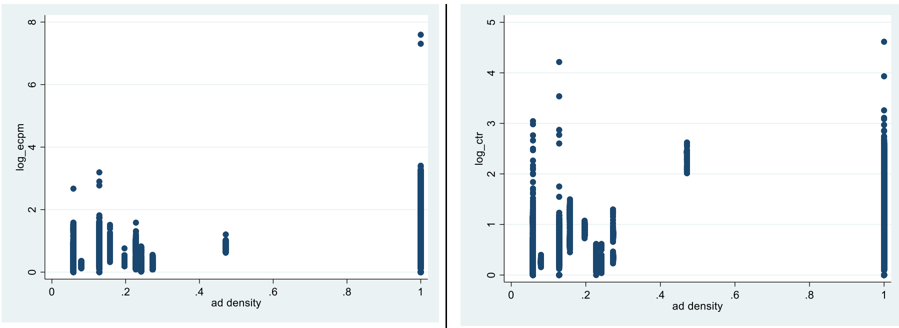
3.3.1 Influence of Advertisement Density on Advertising Revenue and Effectiveness

First, a scatter plot was drawn to briefly describe the relationship between advertisement density and eCPM (or CTR). Figure 7 shows the scatter plot of each variable, and eCPM and CTR are slightly larger when advertisement density is large.

The regression model, including the application dummy variable and time dummy variable, was employed to control seasonality and application-specific effectiveness, and estimate the detailed effect of advertisement density on eCPM and CTR, where Γ_i is the application dummy variable, and Φ_t is the time dummy variable.

$$\ln(CTR_{it}) = \beta_0 + \beta_1 \times AdDensity_{it} + \Gamma_i + \Phi_t + \epsilon_{it} \quad \text{<Equation 1>}$$

$$\ln(eCPM_{it}) = \beta_0 + \beta_1 \times AdDensity_{it} + \Gamma_i + \Phi_t + \epsilon_{it} \quad \text{<Equation 2>}$$



Ad Density – ln(eCPM) Ad Density – ln(CTR)

Figure 7. Scatter plot of eCPM and CTR

The results show that eCPM increased by 44.9%, and CTR increased by 42.8% at $p < .05$, when advertisement density increased by one unit (See Table 6). Therefore, H1.a. and H1.b. are supported. Although the increase rate of eCPM and CTR according to advertisement density was expected to be different, the actual increase rate was similar.

Table 6. Positive effect of advertisement density on eCPM and CTR

	(1)	(2)
DV	ln(eCPM)	ln(CTR)
AdDensity	0.449^{***} (0.014)	0.428^{***} (0.012)
App Dummy	Included	Included
Time Dummy	Included	Included
Constant	0.146^{***} (0.043)	0.143^{**} (0.055)
No. of Observations	16,817	16,817
R^2	0.746	0.601

Robust standard errors in parentheses
* $p < .05$, ** $p < .01$, *** $p < .001$

3.3.2 Heterogenous Influence with the Same Advertisement Density

1) Difference in advertising performance between banner ads and native banner ads

Among all mobile ad formats, only banner ads and native banner ads were selected. The number of observations of banner ads was 3,696, and that of native banner ad was 2,599. Banner ads were set as the base model.

The results show that eCPM increased by 8.1%, and CTR increased by 33.8% at $p < .05$ when using native banner ads rather than banner ads (See Table 7). Therefore, H2.a. is not supported, although the two ad formats with the same advertisement density and UX showed a difference in eCPM and CTR.

The difference in CTR was larger than that of eCPM, showing that native banner ads are a type of ad formats with high effectiveness but low cost from an advertiser's perspective. From the mobile publisher's perspective, although native banner ads still have higher advertising revenue than banner ads, the advertising revenue of native banner ads may increase if the discrepancy between eCPM and CTR becomes much smaller in the future.

$$\ln(CTR_{it}) = \beta_0 + \beta_1 \times NativeBannerAd_{it} + \Gamma_i + \Phi_t + \epsilon_{it} \quad \text{<Equation 3>}$$

$$\ln(eCPM_{it}) = \beta_0 + \beta_1 \times NativeBannerAd_{it} + \Gamma_i + \Phi_t + \epsilon_{it} \quad \text{<Equation 4>}$$

Table 7. Higher CTR and eCPM of native banner ads compared to banner ads

	(1)	(2)
DV	ln(eCPM)	ln(CTR)
NativeBannerAd	0.081***	0.338***
	(0.009)	(0.011)
App Dummy	Included	Included
Time Dummy	Included	Included
Constant	0.403***	0.417***
	(0.087)	(0.064)
No. of Observations	6,295	6,295
R^2	0.562	0.525
Robust standard errors in parentheses		
* $p < .05$, ** $p < .01$, *** $p < .001$		

2) Difference in advertising performance among native interstitial ads, interstitial ads and rewarded video ads

The advertisement density of native interstitial ads, interstitial ads, and rewarded video ads were all equal to 100%. This analysis selected three ad formats with an advertisement density of 100% to check whether eCPM and CTR were consistent among ad formats with the same density. The number of observations of native interstitial ads was 2,190, and those of interstitial ads and rewarded video ads were 1,775 and 1,447, respectively. Native interstitial ads were set as the base model.

The results show that eCPM increased by 128.8%, and CTR increased by 113.1% at $p < .05$ when using interstitial ads; eCPM increased by 178.8%, and CTR increased by 42.4% at $p < .05$ when using rewarded video ads, compared to native interstitial ads (See Table 8).

Therefore, H2.b. is not supported. As in the previous experiment of using banner ads and native banner ads, eCPM and CTR showed differences, even though they had the same advertisement density.

$$\ln(CTR_{it}) = \beta_0 + \beta_1 \times InterstitialAd_{it} + \beta_2 \times RewardedVideo_{it} + \Gamma_i + \Phi_t + \epsilon_{it}$$

<Equation 5>

$$\ln(eCPM_{it}) = \beta_0 + \beta_1 \times InterstitialAd_{it} + \beta_2 \times RewardedVideo_{it} + \Gamma_i + \Phi_t + \epsilon_{it}$$

<Equation 6>

Table 8. The highest CTR of interstitial ads and the highest eCPM of rewarded video ads

	(1)	(2)
DV	ln(eCPM)	ln(CTR)
InterstitialAd	1.288*** (0.015)	1.131*** (0.019)
RewardedVideo	1.788*** (0.016)	0.424*** (0.018)
App Dummy	Included	Included
Time Dummy	Included	Included
Constant	0.391*** (0.038)	0.373** (0.118)
No. of Observations	5,412	5,412
R^2	0.741	0.607
Robust standard errors in parentheses * $p < .05$, ** $p < .01$, *** $p < .001$		

3.3.3 Heterogenous Influence of Disclosure Position

Position dummy variables were added to consider the effect of disclosure position with the same advertisement density. The base model comprised banner ads located at the top of the screen.

The results show that eCPM increased by 9.3%, and CTR decreased by 5.9% at $p < .05$ when the advertisement was located in the middle of the screen; eCPM increased by 24.9%, and CTR increased by 18.3% at $p < .05$ when the advertisement was located at the bottom of the screen (See Table 9). Therefore, H3.a. and H3.b. are not supported.

$$\ln(CTR_{it}) = \beta_0 + \beta_1 \times BannerAd_{it} + \beta_2 \times PositionMiddle_{it} + \beta_3 \times PositionBottom_{it} + \Gamma_i + \Phi_t + \epsilon_{it}$$ <Equation 7>

$$\ln(eCPM_{it}) = \beta_0 + \beta_1 \times BannerAd_{it} + \beta_2 \times PositionMiddle_{it} + \beta_3 \times PositionBottom_{it} + \Gamma_i + \Phi_t + \epsilon_{it}$$ <Equation 8>

Table 9. The highest CTR and eCPM of the "bottom" disclosure position

	(1)	(2)
DV	ln(eCPM)	ln(CTR)
NativeBannerAd	0.238***	0.580***
	(0.025)	(0.028)
PositionMiddle	0.093***	-0.059*
	(0.024)	(0.028)
PositionBottom	0.249***	0.183***
	(0.008)	(0.012)
App Dummy	Included	Included
Time Dummy	Included	Included
Constant	0.154	0.234***
	(0.087)	(0.065)
No. of Observations	6,295	6,295
R^2	0.569	0.541

Robust standard errors in parentheses
* $p < .05$, ** $p < .01$, *** $p < .001$

3.3.4 Heterogeneous Influence by Disclosure Method

The dataset from the same ad format of native ads was analyzed to estimate the effect of disclosure method. Unlike other ad formats, native ads could be expressed as three disclosure methods to be tested in this experiment. Although disclosure methods were different, the ad format of native ad was controlled. The number of observations for "Separated Area," "List UI," and "Pop-up" were 2,190, 2,190, and 730, respectively.

"Separated Area" was set as the base model. The results show that eCPM increased by 13.8%, and CTR increased by 7.9% at $p < .05$, when the disclosure method was "List UI;" eCPM increased by 32.8%, and CTR increased by 141.1% at $p < .05$, when the disclosure method was "Pop-up" (See Table 10). These results imply that the "Pop-up" method is better for increasing eCPM and CTR than the "List UI" or "Separated Area" methods. Therefore, H4.a. and H4.b. are supported.

$$\ln(CTR_{it}) = \beta_0 + \beta_1 \times List_{it} + \beta_2 \times PopUp_{it} + \Gamma_i + \Phi_t + \epsilon_{it} \qquad \text{<Equation 9>}$$

$$\ln(eCPM_{it}) = \beta_0 + \beta_1 \times List_{it} + \beta_2 \times PopUp_{it} + \Gamma_i + \Phi_t + \epsilon_{it} \qquad \text{<Equation 10>}$$

Table 10. The highest CTR and eCPM of the "Pop-up" disclosure method

	(1)	(2)
DV	ln(eCPM)	ln(CTR)
List	0.138^{***} (0.007)	0.079^{***} (0.003)
PopUp	0.327^{***} (0.011)	1.411^{***} (0.028)
App Dummy	Included	Included
Time Dummy	Included	Included
Constant	0.154^{*} (0.064)	0.224^{*} (0.100)
No. of Observations	5,110	5,110
R^2	0.210	0.717

3.4 Discussion

Table 11 summarizes the results of previous experiments. In the first experiment, the relationship between advertisement density and revenue, and advertisement density and effectiveness were analyzed. The results show that H1.a. and H1.b. are supported. eCPM and CTR increased as advertisement density increased. Empirically, the rate of increase of eCPM and CTR according to advertisement density (42.8%, and 44.9%, respectively) by an increase of 1 unit of density, was expected to be different but showed a similar rate of increase.

These results imply that mobile publishers receive a reasonable revenue from advertisers, as much as the proportion of areas devoted to advertisers through mobile advertisements.

In the second experiment, the existence of a difference in advertising revenue and effectiveness was analyzed according to ad formats when advertisement density was similar or the same. The results show that H2.a. and H2.b. are not supported. In H2.a., native banner ads had higher eCPM and CTR than banner ads despite similar advertisement density. In H2.b., eCPM was the highest in rewarded video ads, and CTR was the highest in interstitial ads, despite having the same density.

Native interstitial ads showed the lowest values of eCPM and CTR. The results of H2.a. and H2.b. show that the mobile publisher can earn a higher revenue when selecting native banner ads and adding advertisements with low advertisement density, and rewarded video ads when considering high advertisement density.

Table 11. Summary of experiments

Hypothesis	Result	Discussion
Hypothesis 1.a. As ad density increases, ad revenue (eCPM) increases. ***Hypothesis 1.b.*** As ad density increases, advertising effectiveness (CTR) increases.	• H1.a. and H1.b. are supported. • As ad density increases, both eCPM and CTR increase.	• The rate of increase of eCPM and CTR was expected to be different, but they increased to a similar level. • Mobile publishers earn reasonable revenue from advertisers as providing ad density.
Hypothesis 2.a. Ad revenue (eCPM) and advertising effectiveness (CTR) will be similar between banner ads and native banner ads with similar ad density. ***Hypothesis 2.b.*** Ad revenue (eCPM) and advertising effectiveness (CTR) will be similar between interstitial ads, native interstitial ads and rewarded video ads with the same ad density.	• H2.a. and H2.b. are not supported. • The Native Banner Ad has higher eCPM (8.1%), CTR (33.8%) than the Banner Ad. • eCPM has the highest Rewarded Video Ad (178.8%) CTR has the highest Interstitial Ad (113.1%).	• Ad revenue can be different depending on the ad format used, even with the same ad density • Native banner ads for planning low ad density • Rewarded video ads for planning high ad density
Hypothesis 3a. A disclosure position at the top of the screen has a positive influence on ad revenue (eCPM). ***Hypothesis 3b.*** A disclosure position at the top of the screen has a positive influence on advertising effectiveness (CTR).	• H3.a. and H3.b. are not supported. • Highest results for both eCPM (24.9%) and CTR (18.3%) When placed at the bottom of the screen.	• Users are more aware of the ads exposed at the top, but more likely to click on the ads exposed at the bottom • Thumb zone (Hoover, 2011)
Hypothesis 4.a. “Pop-up” has the highest ad revenue (eCPM) among “Separated area”, “List UI” and “Pop-up”. ***Hypothesis 4.b.*** “Pop-up” has the highest advertising effectiveness (CTR) among “Separated area”, “List UI”, “Pop-up”.	• H4.a. and H4.b. are supported. • eCPM (141.1%) and CTR (32.8%) were the highest for “Pop-up”.	• “Pop-up” is expected to have a positive effect on advertising effectiveness and ad revenue because it has the same effect as stopping users from using the service or content.

In native banner ads, differences between CTR and eCPM were noted, despite the two ad formats having similar densities. Compared with banner ads, the difference in advertising effectiveness was greater than that of revenue, especially in CTR. From an advertiser's perspective, native banner ads are a type of ad formats with high effectiveness but low cost. From a mobile publisher's perspective, even though native banner ads still have higher advertising revenue than banner ads, the revenue of native banner ads may increase if the discrepancy between eCPM and CTR becomes much smaller in the future.

Native interstitial ads showed the lowest eCPM and CTR. Their advertising components cannot physically fill all screens, as shown in Figure 8. Considering only advertisement placement, three ad formats, namely, interstitial ads, native interstitial ads, and rewarded video ads apparently had similar advertisement density, but the advertisement density of native interstitial ads was lower than that of the two other ad formats, in terms of the content area.

Figure 8. Example of native interstitial ads

Engaging points were observed between interstitial ads and rewarded video ads. A comparison of the two ad formats of CTR and eCPM showed that the CTR of interstitial ads was significantly higher than that of rewarded video ads, but that the eCPM of rewarded video ads was higher than that of interstitial ads. Interstitial ads are classified as non-rewarded ads, whereas rewarded video ads are classified as rewarded ads. When non-rewarded ads are exposed, the user's genuine interest and involvement are reflected. Conversely, among users exposed to rewarded video ads, many so-called "cherry pickers" watch advertisements only for reward purposes, and thus have low response (CTR).

Nevertheless, the higher eCPM of rewarded video ads compared with interstitial ads, which means advertisers' high willingness to pay, may reflect advertisers' higher valuation of compulsory 30-second video viewing, one of the characteristics of rewarded video ads. Alternatively, the advertising supply of rewarded video ads is not as adequate as that of interstitial ads; therefore, the valuation of rewarded video ads could be overestimated. Future studies on differences between interstitial ads and rewarded video ads could have great significance given the various issues described above.

In the third experiment, the analysis concerned whether eCPM and CTR differ depending on disclosure position, despite having the same advertisement density. The results show that H3.a. and H3.b. are not supported. Previous research by Nielsen (2006) and Shrestha and Lenz (2007) showed that CTR is higher when ads are placed at the bottom of the screen than at the top of the screen, as opposed to the conclusion that advertisements at the top left are more easily perceived by users.

These results can be explained in various ways, but the most convincing argument is found in Hoover (2011), who found that 49% of people use a smartphone with one hand and lean on their thumbs. Clark (2010) published a survey showing that 75% of people interact with their thumbs. Based on these previous studies, the results of applying the area where the thumb can reach the smartphone and dividing it into comfortable (natural), stretchable (stretching), and uncomfortable (hard) are illustrated in Figure 9.

Figure 9 shows that in a mobile environment, where input occurs mainly by using the fingers, the disclosure position of the advertisement is also advantageously located within the “thumb zone” for user reactions such as clicks to occur smoothly. Although the area at the top of the screen is easily noticed by the user, clicking occurs more easily at the bottom of the screen, which is the thumb zone. Advertising revenue and effectiveness of this disclosure position increases with more clicks at the bottom of the screen.

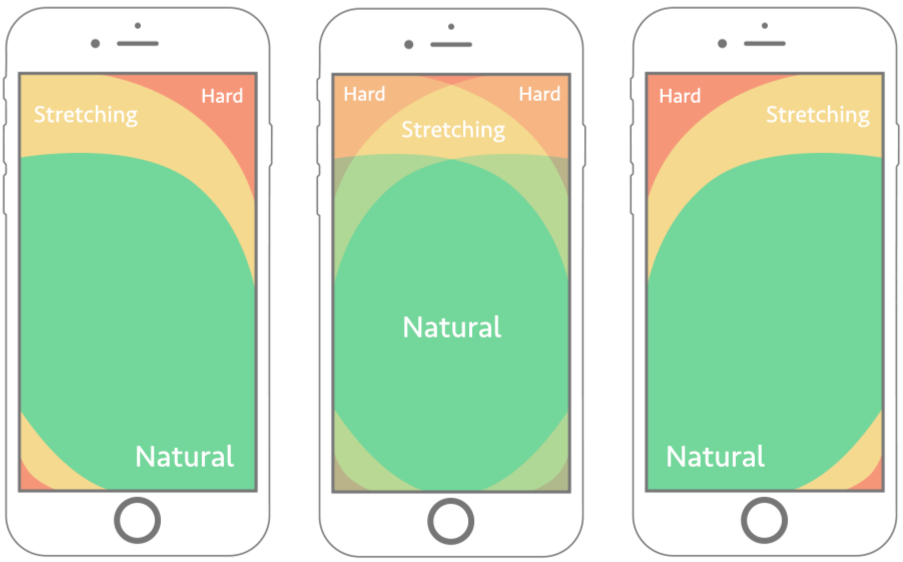


Figure 9. “Thumb Zone”, where clicking occurs more easily using the fingers

The display screen of mobile devices is becoming larger. Therefore, many mobile app developers and companies such as Google and Facebook utilize the bottom of the screen more than before for key service features such as the navigation bar and key action button. Figure 10 shows an example of a modified UX guideline for Facebook.

The final experiment was conducted to examine the difference between advertising revenue and advertising effectiveness according to disclosure method, despite the same ad format. As a result, although ad formats were the same, CTR and eCPM showed significant differences when exposed as "Pop-up." In advertisements expressed as "Pop-up," a positive influence was expected in terms of advertising effectiveness owing to effects such as being displayed as inserts and interrupting the user's experience of services or contents.

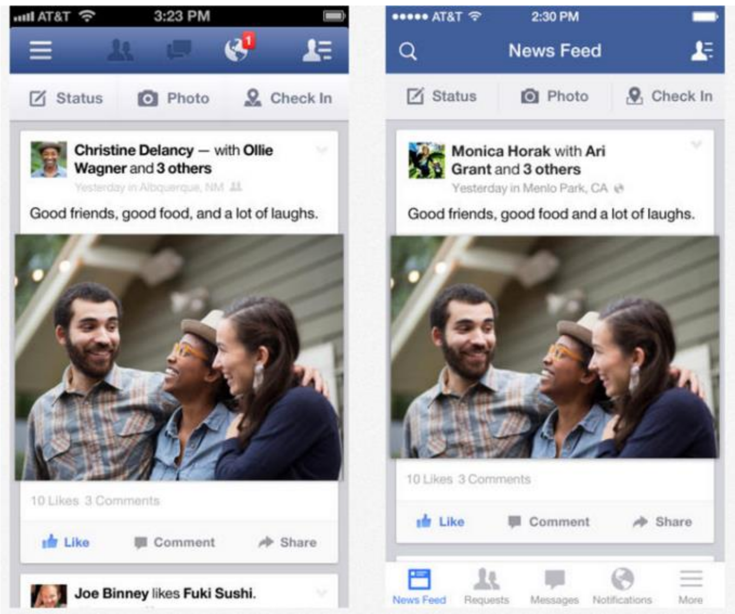


Figure 10. Example of changes to navigation at the bottom of the screen

By contrast, when considering advertisement placements of sample mobile app, “1km” and “Meeff” which exposed advertisement inside the content of “List UI”, advertisements were repeatedly exposed for every fifth or tenth small unit. Advertisement placements were displayed to users repeatedly and could influence a decrease in advertising effectiveness, similar to the phenomenon of “banner blindness.”

Chapter 3 analyzes advertising factors and the relationship between them to consider what occurs when mobile publishers wish to add mobile ads to their services and focus on new factors, namely, advertisement density, disclosure position, disclosure method, relation to native ads, and rewarded video ads, which have been recently introduced.

Once mobile publishers determine advertisement placement and ad format, a waterfall bidding strategy should be established and operated to maximize advertising revenue. Therefore, Chapter 4 analyzes history transaction data, plots demand curves of each ad network, optimizes the waterfall bidding strategy, and develops guidelines for maximizing advertising revenue.

Chapter 4. Waterfall Strategy Development

4.1 Introduction

When mobile app developers attempt to sell their advertisement requests or inventory to an ad network, they usually review one or two ad networks such as Google's AdMob and Facebook Audience Network. If a mobile app's traffic is too low, a small amount of revenue is expected; therefore, mobile app developers may decide not to sell their advertisement inventory to ad networks. Table 12 describes how ad networks are applied by mobile apps to monetize through advertising with respect to traffic size as the mobile app grows. In the initial stage (i.e., Stage 1), which consists of creating, distributing, and testing the usability of the application while recruiting users, business is conducted using its funds, rather than by depending on the revenue earned from advertising. As traffic grows beyond this stage (e.g., more than 10,000 daily active users), the first phase of monetizing through advertisement occurs as the advertisement placement starts to sell through an ad network. This stage is monetization (i.e., network-level Stage 2). Given the lack of knowledge on monetizing through advertising and the dependency on a single network, the owner cannot determine the price, but the network suggests the bid price according to which the transaction proceeds. Next, Stage 3 is the first stage at which multiple ad networks are used: more advertisements can be provided, and additional networks need to be secured to receive sufficient serving (i.e., receive more demand) and meet service traffic. At this stage, the reserve price (or floor price), which is the minimum selling price that must be set for each ad network, plays an important role. This value is the minimum price at which a publisher is willing to sell its advertisement inventory in real-time bidding markets and contributes to the reduction of bidding transactions by dropping overly low bids from multiple advertisement inventory buyers (Li et al., 2018).

At Stage 3, a low reserve price will be set because an ordinary publisher has less negotiation power in the global duopoly ad networks. Therefore, a bidding strategy must be formulated for each ad network. Generally, mobile environments with low computing power of mobile devices and low speed and stability of networks cannot support sufficient real-time bidding transactions. Operating header bidding for multiple ad networks is difficult, and mobile publishers usually follow the waterfall bidding method, which requires relatively low performance of environments. Therefore, before a supply-side platform (hereinafter "SSP") receives an advertisement request from a mobile publisher, it should establish the order and reserve price of each network. At Stage 4, a mobile publisher adds more ad networks to maintain the fill rate, that is, the number of served advertisements divided by the number of requests, as service traffic increases owing to higher network management costs.

This chapter defines several problems of multiple network management and proposes a waterfall bidding strategy that maximizes the advertising revenue of mobile publishers. For the empirical data analysis, the bidding situation to maximize the advertising revenue of mobile publishers was theoretically organized based on a case study of AD(X) Inc. (hereinafter “AD(X)”), the leading SSP company in South Korea. Methods of establishing an ad network call order and reserving the price in a waterfall bidding situation were devised by analyzing advertisement inventory transaction history data. This study proposes a dynamic reserve pricing strategy that performs significantly better than the reserve pricing strategy, based on the historical average previously used by AD(X).

Table 12. Publisher traffic and use of ad networks

Stage	Description (example)	Size of Inventory Traffic	Number of Ad Networks	Winning Bid	Reserve Price
1	The mobile app's service traffic is too low to be monetized by ad networks	very low	none	none	none
2	The mobile app starts to use a single ad network (e.g., GDN of FAN) to display an advertising banner on its inventory	low	1 (single)	one and only	low
3	The mobile app increases the number of ad networks to have a higher chance of displaying advertising banners	middle	2-3 (multiple)	the first bid that meets the reserve price (not optimized)	middle
4	The mobile app needs every accessible ad network to optimize its ad revenue	large	4-7 (multiple)	the first bid that meets the reserve price (not optimized)	high

4.1.1 Information Asymmetry

Publishers seek to monetize user traffic at certain times and generate advertising revenue by setting prices that are higher than the reserve price for slots that can be sold instantaneously by sending requests to the ad network. The problem is that the publisher does not determine the price; the ad network does but does not provide the publisher with any information on the price or the valuation process of each user and advertisement request. It only provides the statistics of transactions made during a certain period (e.g., every three hours or daily). Given this information asymmetry, determining an optimal price that maximizes the publisher's advertising revenue is not possible when determining the reserve price for ad networks from the publisher's side. Waterfall bidding through a 1:N structure is sequentially applied between the publisher and ad networks. The general auction is applied in favor of the publisher, who can always select the highest bid, but bidding transactions are executed in the order that advertisement requests are made during waterfall bidding. Therefore, if an ad network that could have been served at a higher price is not prioritized, a loss is generated by an ad network that suggests the second highest price but receives the first advertisement request (Ghosh et al., 2009).

From the publisher's point of view, information asymmetry exists because the ad network does not release the bid price for the traffic of individual users, and publishers are compelled to sell the advertisement slot to relevant users at a lower price, in the end. Two decisions should be made to enable publishers to sell their advertisement inventory at a higher price using the waterfall method: 1) selecting and ad network for the first advertisement request and 2) determining the reserve price. This study proposes methods for managing these two factors in a situation of information asymmetry, to maximize the publisher's profits.

4.1.2. Bidding Strategy

Waterfall bidding and header bidding are commonly employed when SSPs participate in auctions (Afshar et al., 2019). Advertisement requests from publishers are delivered simultaneously to multiple networks during header bidding (Sayedi, 2018). In waterfall bidding (or waterfall strategy), a publisher's advertisement requests are sequentially delivered to the network, and they last until the advertisement is found or the session times out (Wang et al., 2017). In Figure 11, the third stage depicts an example of waterfall bidding. First, the reserve price and advertisement request are sent to the first ad network assumed to have the highest price. Once the offer is accepted by the first ad network, the advertisement contents are provided via software development kit (SDK) and then displayed on the user's screen, thus ending the waterfall bidding. If the transaction with the first ad network is unsuccessful (i.e., including cases in which time runs out because no response is received), it goes through the same process with the second network. The last network sets the lowest reserve price to reduce the chance that the advertisement is missed, thus ensuring that the default advertisement is displayed.

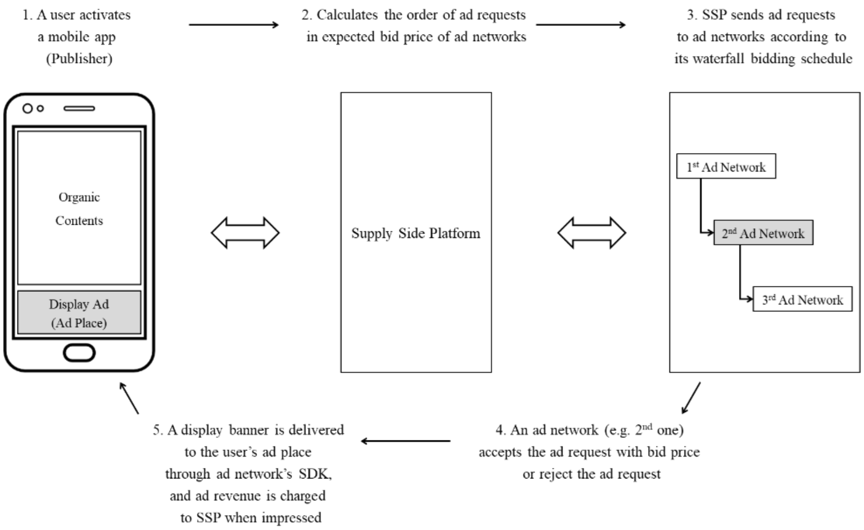


Figure 11. How a mobile app receives a display ad from ad networks

For header bidding to operate smoothly, advertisement requests must be sent to numerous networks within a short period of time, and responses must be received during this time frame. Therefore, the performance of the device and network where the advertisement will be published must be high. Header bidding is used in high-performance environments such as PCs or servers, whereas the waterfall method is employed in mobile environments, where performance is relatively low.

Another advantage of the waterfall model compared with header bidding is that higher user traffic of the mobile publisher will make it easier to obtain adequate advertisement serving. For instance, if several advertisement requests are generated in a device in a day as requests are continuously sent to an ad network or exchange, the price decreases over time, culminating in the decline of the fill rate (rate of advertisements provided to requests) because the advertisers or DSPs participating in the auction expect requests to be made again in the future and do not bid at a high price. In this situation, the use of header bidding to operate advertisement requests represents the same environment as the use of a single ad network, and the publisher's profits are negatively affected in the long run. However, making sequential advertisement requests to numerous networks using the waterfall method can have the effect of sending relatively fresh (or rare) requests to each network.

This study suggests a method for optimizing the values to set as priorities for each ad network and reserve price based on understanding the characteristics of the waterfall bidding strategy to maximize the advertising revenue of mobile publishers.

4.1.3. Price and Demand

The relationship between price and demand has been theoretically established (Friedman, 1949), and numerous studies concerning economic modeling of demand estimation have been conducted. Equation 1 shows the relationship between two main variables—price and demand—whereby a 1% increase in demand affects beta% change in price, and alpha means the constant term.

$$\ln(\text{price}) = \alpha + \beta \cdot \ln(\text{demand}) + \varepsilon \qquad \text{<Equation 11>}$$

Figure 12 is a scatter plot of the transaction price (eCPM) and quantity of advertisements sold (impressions) daily to an ad network (MoPub) by a specific publisher (Smart Delivery) from January 1, 2019 to June 30, 2019; based on this dataset, a demand curve can be drawn. Here, price elasticity (or E_p^d) can be calculated. Three sections categorizing price elasticity can be defined as follows: $E_p^d > 1$ (elastic), $E_p^d = 1$ (unit elastic), and $E_p^d < 1$ (not elastic). In terms of operation strategy, in the elastic section, the relative change in demand is greater when the price changes; thus, the revenue estimated by price*demand is more likely to decrease. By contrast, in the non-elastic section, the relative change in demand is small although the price changes; thus, the revenue risk is lower.

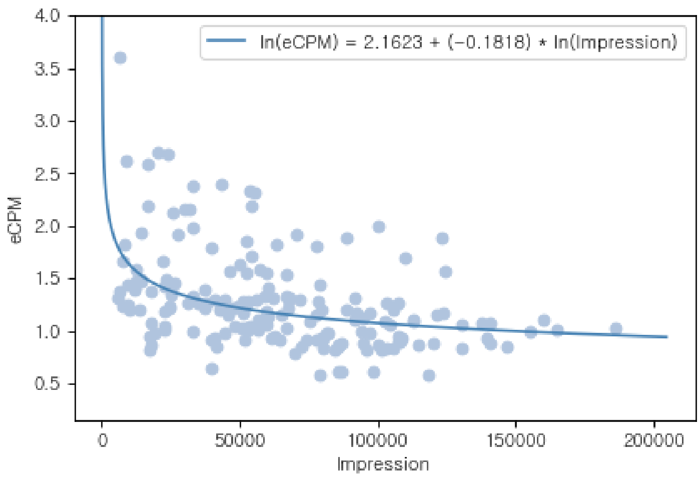


Figure 12. Example of an ad network's demand curve

4.2 Estimation of Ad Networks' Demand Curves

4.2.1 Dataset

The publisher-advertisement type-ad network-level daily panel data collected from AD(X) of South Korea for one year from January 1, 2019 to December 31, 2019 were used in this study. Each record consisted of a daily real-time bidding history, whose attributes were impressions and eCPM [=(revenue/impressions)/1,000], aggregated by operating system (OS), mediation type, and ad network.

OSs were classified as Android and iOS, mediation type as AdMob and MoPub, and ad networks as AdManager, Facebook, AdMob, and MoPub. Descriptive statistics are shown in Tables 13, 14, 15, and 16.

When making a bid, AD(X) sets different reserve prices by OS type, mediation type, and ad network. This chapter observes which candidate period is the best for predicting reserve prices. Comparing the superiority between the demand curve models derived over each period helps in determining the optimal model for future strategic planning. Given this background, the recent one, two, three, and four weeks of datasets were used to determine a demand curve with high accuracy.

Table 13. Descriptive statistics of the full dataset

Variable	Obs.	Mean	Std. Dev.	Min	Max
eCPM	59,964	2.38	11.15	0.000753	1,988.22
Impressions	59,964	133,781.61	1119886.60	1	24,579,239

Table 14. Descriptive statistics by operating system type

OS Type	Variable	Obs.	Mean	Std. Dev.	Min	Max
Android	eCPM	35,075	2.5331	14.1060	0.0037	1988.2220
	Impressions	35,075	200,376	1,458,463	1	24,579,239
iOS	eCPM	24,889	2.1580	4.3899	0.0008	87.7057
	Impressions	24,889	39,933	94,264	1	1,092,638

Table 15. Descriptive statistics by mediation type

Mediation Type	Variable	Obs.	Mean	Std. Dev.	Min	Max
AdMob	eCPM	2,465	14.5648	50.2762	0.0529	1988.2220
	Impressions	2,465	3,899	6,739	1	66,028
MoPub	eCPM	57,499	1.8549	3.8462	0.0008	182.5000
	Impressions	57,499	139,350	1,143,309	1	24,579,239

Table 16. Descriptive statistics by ad network

Ad Network	Variable	Obs.	Mean	Std. Dev.	Min	Max
Ad Manager	eCPM	13,302	1.5275	1.6700	0.0106	20.0000
	Impressions	13,302	59,124	276,854	1	10,344,888
AdMob	eCPM	15,527	3.0662	20.7164	0.0067	1,988.2220
	Impressions	15,527	36,214	83,248	1	1,772,837
FaceBook	eCPM	15,783	3.9809	6.4105	0.0008	47.2200
	Impressions	15,783	24,012	102,694	1	2,768,493
MoPub	eCPM	15,352	0.7687	0.9698	0.0321	10.1881
	Impressions	15,352	410,000	2,170,586	1	24,579,239

4.2.2 Demand Curve Estimation

A demand curve is a graph that describes the relationship between the price for a product and the amount of demand generated by that price. This study attempts to utilize demand curves to establish waterfall bidding strategies. In our model, advertising impressions and eCPM (the dependent variable) are used to interpret the relationship between the quantity and price of a demand curve. Data collected from a single publisher cannot explain the entire demand in the market, but the relative difference in demand between ad networks alone can be expected to help individual publishers build their strategies. The demand curve is an important deterministic factor when setting the price for a certain product, and the revenue (or profit) of a company can be determined based on this graph. In this regard, just as companies use the demand curve in pricing decisions, the relationship between eCPM and impressions may allow publishers to establish a pricing strategy that can increase sales of real-time bidding. Determining the maximum eCPM for a given impression based on the demand curve enables publishers to set proper reserve prices and maximize their revenue.

This relationship between eCPM and impressions can be considered a demand curve on the following grounds in real-time bidding transactions: first, small amounts are served at a high price, but larger quantities are usually served at a relatively lower price. This pattern corresponds to the characteristics of demand curves heading downward as the demand increases (See Figure 13). Here, the demand curve can be obtained as a set of price-demand pairs served in the same ad network for the same advertisement placement (a specific location where advertisements can be published on a mobile app).

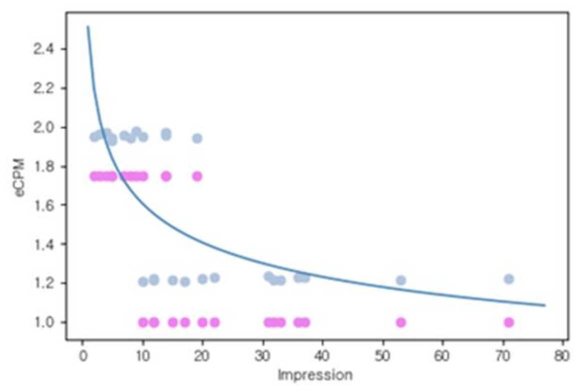


Figure 13. Negative correlation between impressions and eCPM

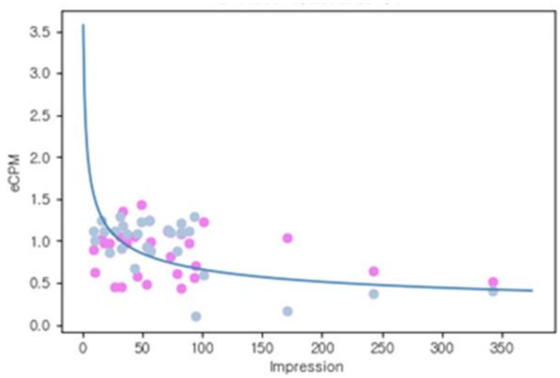


Figure 14. Price-demand pairs existing over a wide range of demand curves

Second, price–demand pairs for the same advertisement place may exist in a wide range of areas instead of focusing around a specific one as prices for each bidding vary due to the influence of different factors (See Figure 14).

Table 17 shows statistics of demand curves estimated from the bidding history divided by date intervals of 7, 14, 21, and 28 days . Each interval corresponds to each group (i.e., Groups 1 to 4) consisting of 8,722, 4,514, 3,045, and 2,403 models, respectively. Each group's average R^2 values were 0.3491, 0.2933, 0.2695, and 0.2768, respectively. Models with a coefficient greater than 0 (i.e., price increases as demand increases) were discarded because they do not meet the basic conditions of demand curves. Each group had 3,692, 1,901, 1,331, and 1,008 models with negative coefficients, and their R^2s were 0.3800, 0.3378, 0.3039, and 0.3088, respectively. The results show that the regression models from the data with intervals of 1 week outperformed those from data with intervals of 2, 3, or 4 weeks (See Table 17).

Table 18, 19, and 20 compare the performance of each model by mobile OS, media type, and ad network, respectively. Only models obtained from the 1-week observation period, showing the highest performance during the various periods, are described.

Table 17. Descriptive statistics by observation period

Group	Observation Period (#Days)	Number of Models	Mean R^2	Mean Coef.	Std. Dev. Coef.	Min. Coef.	Max. Coef.
1	7	3,692	0.3800	-0.4547	0.6728	-7.8856	-0.00004910
2	14	1,901	0.3378	-0.4031	0.5781	-7.2035	-0.00000256
3	21	1,331	0.3039	-0.3798	0.5461	-6.7620	-0.00001332
4	28	1,008	0.3088	-0.3895	0.5486	-6.5466	-0.00004655

Table 18. Descriptive statistics (single week)

OS Type	Number of Models	Mean R^2	Mean Coef.	Std. Dev. Coef.	Min. Coef.	Max. Coef.
Android	2,104	0.3914	-0.5095	0.7648	-7.8856	-0.00004910
iOS	1,588	0.3649	-0.3820	0.5180	-5.0787	-0.00008405

Table 19. Descriptive statistics by mediation type (single week)

Mediation Type	Number of Models	Mean R^2	Mean Coef.	Std. Dev. Coef.	Min. Coef.	Max. Coef.
AdMob	165	0.2791	-0.2771	0.3380	-1.6425	-0.00090160
MoPub	3,527	0.3847	-0.4630	0.6833	-7.8856	-0.00004910

Table 20. Descriptive statistics by ad network (single week)

Ad Network	Number of Models	Mean R^2	Mean Coef.	Std. Dev. Coef.	Min. Coef.	Max. Coef.
Ad Manager	865	0.3271	-0.2325	0.3009	-1.6527	-0.00005700
AdMob	831	0.4479	-0.8171	0.9757	-7.8856	-0.00435175
FaceBook	810	0.3406	-0.3875	0.5409	-3.3896	-0.00004910
MoPub	1,186	0.3979	-0.4086	0.5857	-4.7275	-0.00084550

When bids are made with several ad networks, a distinct demand-price relationship exists for each one. This situation implies that for the same advertisement placement, bids are concluded at a higher price for some ad networks and at relatively lower prices for others. When the bidding order is changed, advertisements may be sold at higher prices using the waterfall bidding method, which allows publishers to bid for different networks sequentially. A publisher can earn more revenue by making the first bid with an ad network that is expected to pay higher prices.

Thus, demand curves of certain advertisement placements estimated for each network from the bidding records could help publishers establish a bidding strategy that is optimized for the goal of maximizing sales. The relationship between different ad networks regarding advertisement placements can be classified as two types of demand curves. The first demand curve shows a higher eCPM in all impression sections than the others, as shown in Figures 15(a) and (b). In Figure 15(a), Ad Manager concludes the bid at a price that is significantly higher than that of AdMob or MoPub. For example, several bids made at $3 at AdMob could have been concluded at a higher price ($6 to $7), if the bid was made at Ad Manager first.

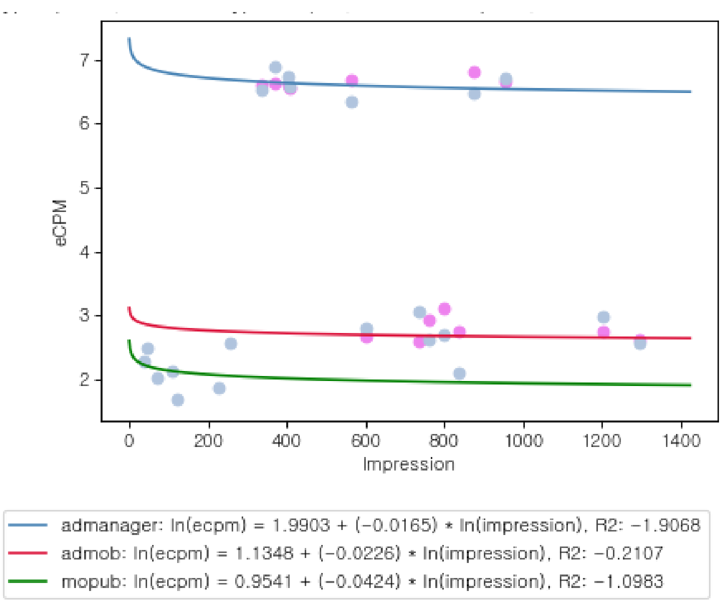


Figure 15a

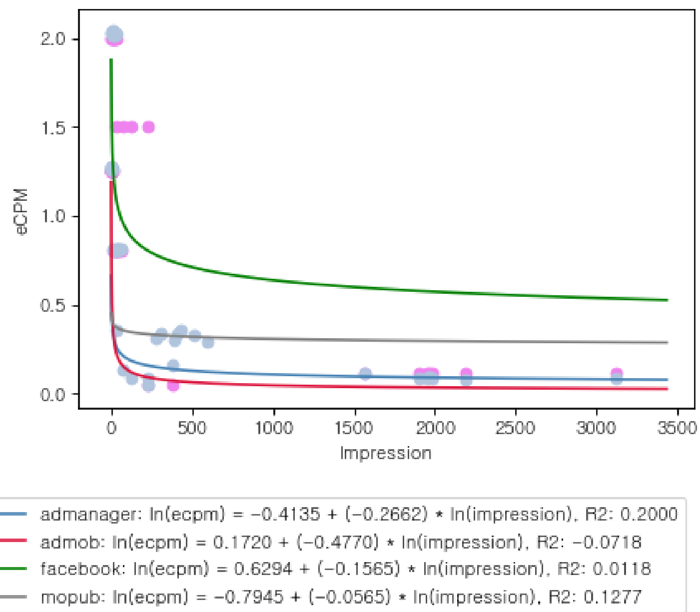


Figure 15b

Figure 15. Demand curves without intersections between ad networks within a bidding interval

Second, Figures 16(a) and (b) show that one demand curve is superior to the other in a certain section, but the other curve becomes superior once it moves away from that section. After each bid with the two different ad networks has been concluded as many as the impression of the intersection between their demand curves, the highest price per impression from each ad network that a company can expect is reversed. Figure 16(a) shows that at quantities less than that of the intersection (impressions < 120), advertisements on Facebook are sold at higher prices and lower quantities, but the winning bid prices on AdMob are higher in the other sections of the quantities (impressions > 120). This finding means that publishers must bid for different ad networks depending on the quantity of the impressions to achieve higher revenue: Facebook on the left side of the intersection and AdMob on the right side. Therefore, bidding first in either of the two sections (left or right side), where the demand curve is higher, will be more advantageous when all other conditions are equal.

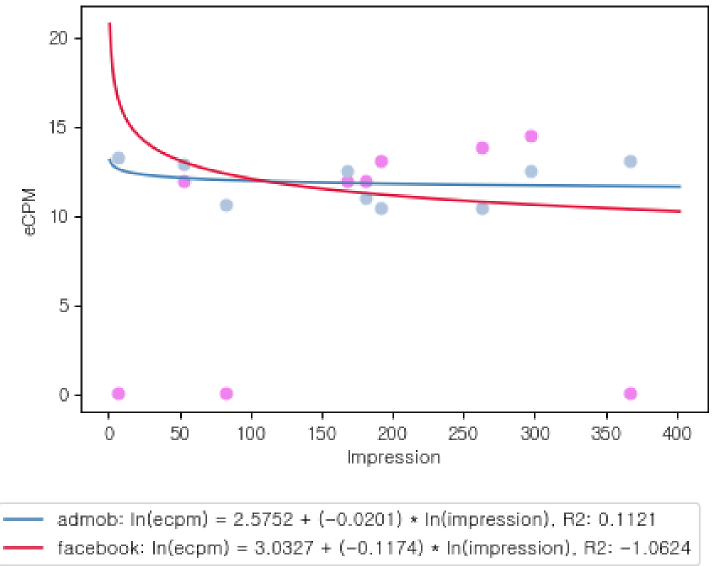


Figure 16a

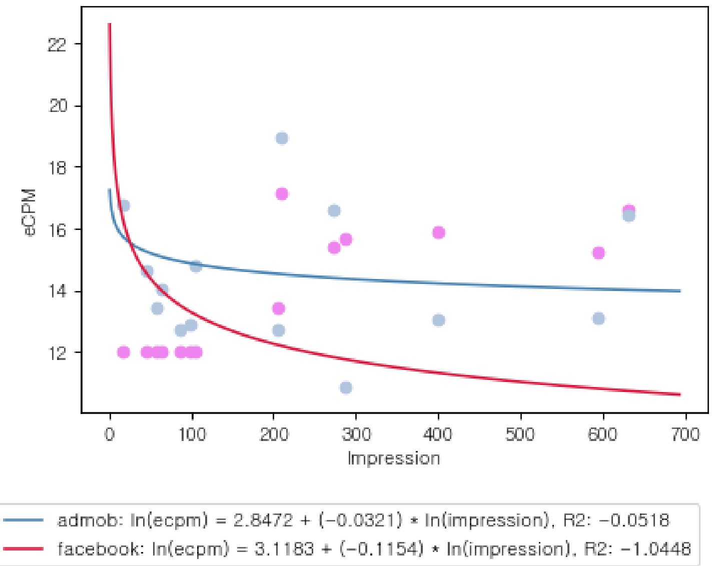
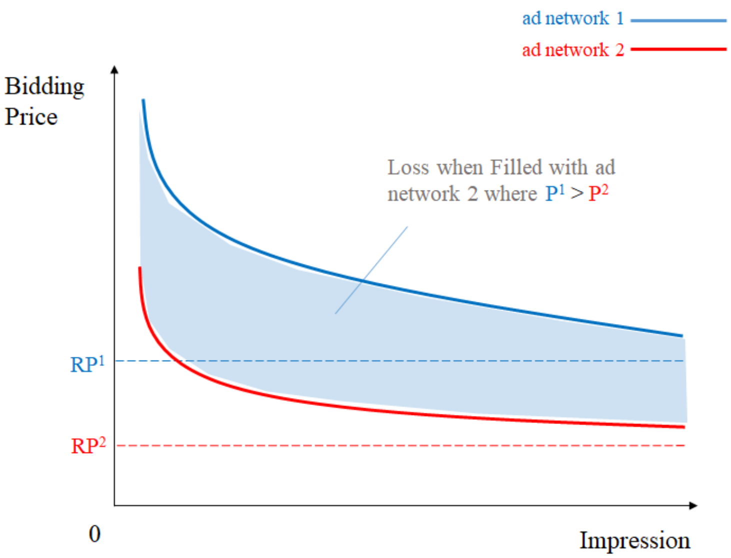


Figure 16b

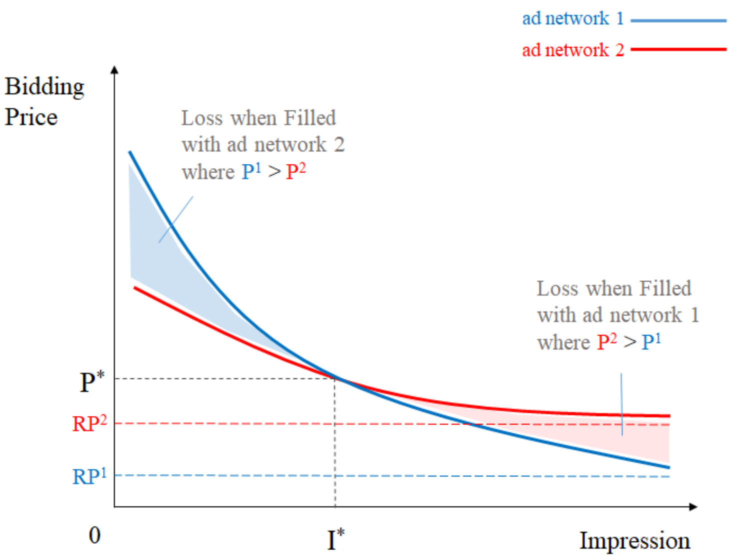
Figure 16. Demand curves with intersections between ad networks within a bidding interval

4.3 Waterfall Bidding Strategy

This section assumes that a publisher has two ad networks, and the distribution (or geometrical position) of two demand curves is known as a result of the demand curve estimation explained previously. In cases with three or more ad networks, all demand curves are commonly assumed to have an ordinal distribution, while one pair of demand curves intersects or not to lower the model's complexity. Therefore, this chapter considers the geometrical position between two demand curves, denoted as ad network 1 and 2. If ad network 1's demand curve has a higher bidding price than that of network 2 the same impression for any impression in an observed interval, two demand curves have a distribution as in the left image of Figure 17. When one demand curve is higher than the other, or when a publisher requests an advertisement impression from ad networks, waterfall bidding proceeds, first with ad network 1, then with ad network 2. If the standards for setting the bid price for the individual user between ad networks 1 and 2 is similar (i.e., both are set at a high or low price), the probability of a loss occurring because of a type 2 error (false negative: ad network 2), as in the left figure, becomes low. However, for a certain individual user, a case could exist, in which ad network 2's bid price > ad network 1's bid price; hence, the loss caused by the mixture of type 1 and type 2 errors may occur, as shown below.



(a) When two demand curves have no intersection



(b) When two demand curves have a cross point

Figure 17. Advertising trading economics between publishers (or SSPs) and ad networks: two situations with and without curve intersections

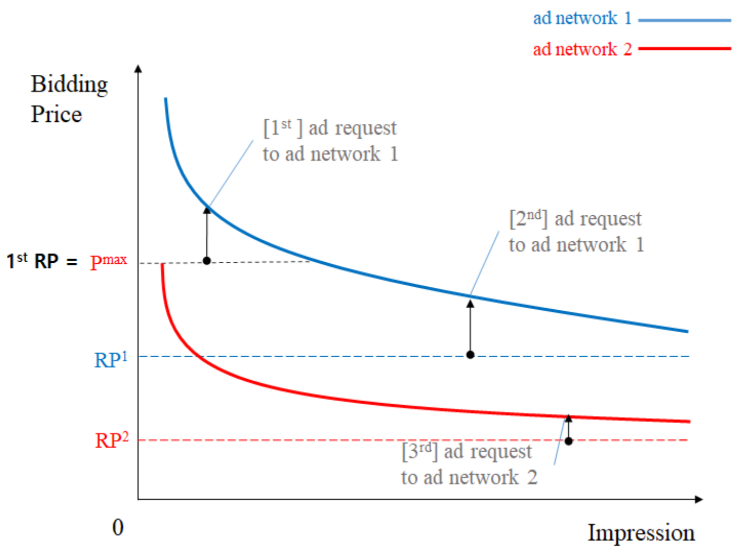
If two demand curves intersect, as shown in Figure 17(b), the sequence of the ad network with the higher price will be different for the left side and right side of the intersection. Instead of simply following the sequence of those with a higher average, this proposal intends to make a request using the contextual bidding strategy by dividing the interval into two sub intervals such as the left side of I* and the right side of I* to follow the sequence of the ad network with a higher price in each sub interval. When the demand curves of two networks overlap, the wider the gap between higher and lower eCPMs in each sub interval, the greater the bid price gap, resulting in a noticeable difference in revenue.

Although the trading price of each user is unknown, demand curves can be drawn as explained previously if the information on the overall trading price during a certain period (e.g., total transaction price and total number of impressions every three hours) is provided. The overall price structure can be understood based on this graph, which can provide clues for making an advertisement request at a higher price. The loss in the blue area of Figure 16 is the revenue loss, namely, $P^1 - P^2$ in waterfall bidding, although the advertisement inventory can be purchased at a higher price by ad network 1. If the advertisement request is made to ad network 2 first, then it is sold at a relatively lower price. Total revenue will decrease by the size of the area indicated in blue owing to this profit loss. Likewise, the red area in the bottom right in the second sub interval shows that ad network 2 can buy an advertisement inventory at a higher price in waterfall bidding, if ad network 1 is prioritized for the advertisement request, but it is sold at a relatively lower price, and the expected revenue loss is equal to $P^1 - P^2$ per transaction.

A step-by-step sales (or advertisement request) strategy that will sell at a higher price is established, as shown in Figure 18, to avoid this type of loss, assuming a known demand curve, where it can be sold to an ad network at a higher price. In Graph (a) on the left, no intersection is observed between ad network 1 at the top and ad network 2 at the bottom. Therefore, the curve above the line "P = P^{max} of the ad network 2," corresponding to ad network 1's demand curve, which always has a price advantage, should be defined as the first bidding interval. For the second interval, which is the "P^{max} of the ad network 2" area, ad network 2 may propose a higher price for a certain individual user. However, probabilistically, ad network 1 has a large interval in which a certain price can be proposed, and setting a second advertisement request as the minimum reserve price for ad network 1 is more reasonable because of the risks or costs that occur owing to the nature of waterfall bidding. This explains the use of the expression "probabilistic approach under information asymmetry." In the second trial, if an advertisement fill response is not received, the minimum reserve price should be set to ad network 2's observed reserve price as a default value, and an advertisement request should be made.

Next, in Figure 18(b), because there is an intersection between two demand curves, an explanation must be provided, compared to Graph (a) mentioned above. By first setting the reserve price = P^{max} of the ad network and making the advertisement request, the highest price will be guaranteed. If the ad fill response is not received, the reserve price should be set to P^* value, which is the intersection of the two demand curves, and an advertisement request should be made for ad network 1.

It is undoubtedly true that there is the possibility that a higher price may be proposed by ad network 2 within that section. However, because the ad network slope is more gradual, as in Graph (a), there is a higher chance that the proposed price will be within that section. When considering the risk and cost that may occur in switching the ad network, one should set the reserve price = P^* and proceed while maintaining contact with ad network 1. Next, if an ad fill response is not received, ad network 2 (with the higher demand curve position) should be set at the observed minimum reserve price as a default value, and an advertisement request should be made as a final attempt.

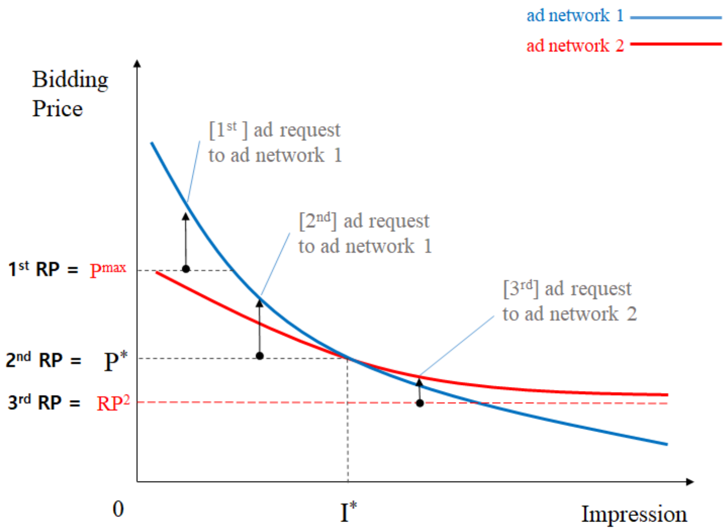


(a) When two demand curves have no cross point

[step1] target ad network = 1 #reserve price = max(ad network 2' bid price)

[step2] target ad network = 1 #reserve price = default value for ad network 1

[step3] target ad network = 2 #reserve price = default value for ad network 2



(b) When two demand curves have a cross point

[step1] target ad network = 1 #reserve price = max(ad network 2' bid price)

[step2] target ad network = 1 #reserve price = bid price at the cross point, P*

[step3] target ad network = 2 #reserve price = default value for ad network 2

Figure 18. Demand curve-based waterfall bidding strategy

4.4. Sensitivity Analysis

In the real world, various situations do not allow for the reproduction of settings while adjusting certain test conditions (e.g., turbulence modeling by Moin and Mahesh 1998), or the collection of various data for major research variables is impossible in certain circumstances. A sensitivity analysis allows for the prediction of test results that cannot otherwise be observed because of realistic restrictions such as data availability. Theoretical research and empirical analysis use simulation methods to secure predicted results for various scenarios based on these advantages (Fleder and Hosanagar, 2009; Park et al., 2012; Park and Han, 2013). Moreover, such an analysis is added to interpret how advertising revenue can be changed by the external environment when a publisher conducts waterfall bidding because decision makers can be trained through business simulation methods (Adobor and Daneshfar, 2006). However, how the advertisement product value is set and how differently the bid price is proposed for an individual user (or mobile device) is difficult to observe. Estimating the selling price for individual users is impossible, from the publisher’s point of view, because of information asymmetry.

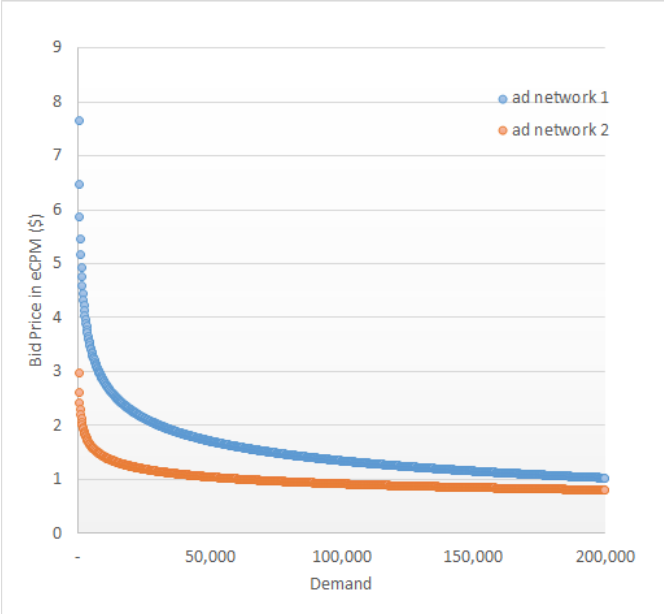
A probability density function is employed, using the demand curve estimation results (i.e., equation 1) to create a distribution for the price that the ad network proposes regarding an individual user’s advertisement slot requested by the publisher and overcome these realistic limitations. The information asymmetry is set as a parameter of sensitivity analysis. And the sensitivity analysis is conducted, because knowing whether two different ad networks tend to make similar evaluations of the same user (i.e., positively correlated) or propose bid prices independent of each other is impossible. Depending on whether the individual decision made by the ad networks is independent or similar, the potential for loss due to type 1 or 2 error differs. Therefore, this study focuses on the degree of performance improvement in each situation, using the demand curve-based waterfall bidding model.

Based on the estimated demand curves generated by regression analysis (see Chapter 3.2), a probability density function is formed by creating a probability distribution that generates bid prices. Then, the numbers are input as values in the inverse function that is expected to be generated by ad networks 1 and 2, to trace the prices obtained through random number generation. Next, ad networks 1 and 2 are assumed to make price bids (e.g., offering eCPM) for each impression, and the revenue strategy performance is compared, based on the demand curve-based waterfall bidding strategy against the ongoing strategy (i.e., historical average). When calculating advertising revenue, the fill rate and show rate through the ad networks are assumed to be the same at 100%, which is deemed reasonable, although the actual number is lower.

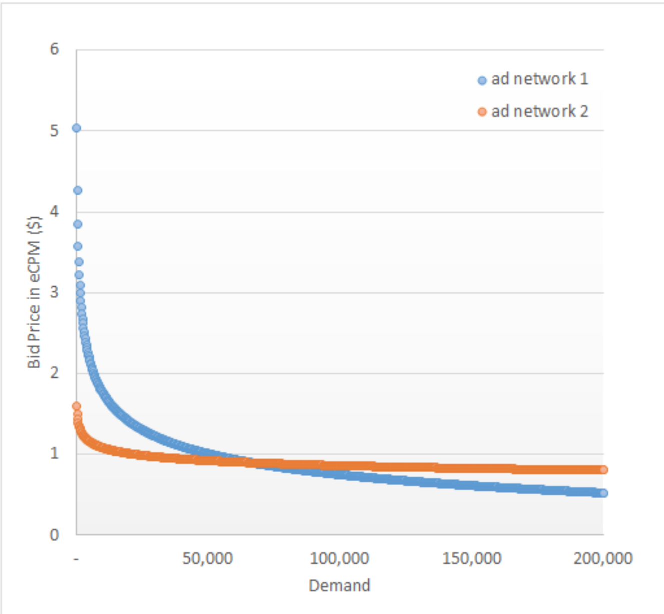
Figure 19 shows each demand curve of two ad networks, when two demand curves have no intersection or cross point. They incorporate parameters of sensitivity analysis and alpha and beta sets, as stated in Table 21. Regarding the alpha and beta of each demand curve, representative parameters are selected to show the two types of demand curve distribution (i.e., with or without intersections). The left and right graphs in Figure 18 show the position of the two demand curves in an actual sensitivity analysis. In Figure 19(b), the point where the demand curves of the two ad networks intersect is explained in Section 4, whereas the demand curves in Figure 19(a) are in order and have no intersection.

Table 21. Parameters of sensitivity analysis

sensitivity analysis Parameters	Descriptions	(a) Values when two demand curves have no intersection	(a) Values when two demand curves have a cross point
Demand curve 1's alpha	Demand curve's constant, estimated by regression analysis	3.27	2.85
Demand curve 1's beta	Demand curve's regression coefficient for ln(impression), estimated by regression analysis	-0.21	-0.19
Demand curve 2's alpha	Demand curve's constant, estimated by regression analysis	2.1	1.00
Demand curve 2's beta	Demand curve's regression coefficient for ln(impression), estimated by regression analysis	-0.19	-0.10
Impressions as daily traffic	Mobile app's daily traffic size	200 ~ 200,000	200 ~ 200,000
Bid price similarity	Correlation coefficient between bid prices, 0 when two bid prices are independent, 1 when two bid prices are positively and perfectly correlated with each other	correlation = 0 ~ 1.0 with step size = 0.1	
Top N% bid price user traffics of ad network 1 or 2	User cases with the bid price in the top N^{th} percentile of an ad network	Ad network 1's N = 10% ~ 100% with step size = 10%	Ad network 2's N = 10% ~ 100% with step size = 10%



(a) When two demand curves have no intersection



(b) When two demand curves have a cross point

Figure 19. Demand curves used in the sensitivity analysis

In Table 21, two sensitivity analysis parameters are defined to predict the proposed model's performance under information asymmetry. First, the top N% of bid price user traffic means user cases with bid prices in the top N^{th} percentile of an ad network. As a basic sensitivity analysis, Top N = 100% is set such that all observable bid prices can be generated on the demand curve. Second, the bid price similarity between the two ad networks is defined. The bid price similarity is the correlation coefficient of the two ad networks' bid prices. For example, a 1.0 value means they are positively and perfectly correlated with each other, and a 0.0 value means the two ad networks' pricing patterns are independent of each other (i.e., no correlation). This parameter setting is advised by the SSP company's trading expert. According to the expert, for an individual user, the ad networks' bid prices have an independent or positively correlated tendency. Thus, the waterfall bidding method are compared through the historical average and proposed model by decreasing the bid price similarity between the two ad networks by 0.1 from 0.0 to 1.0. Table 22 shows the predicted eCPM using each method and the aggregate value of the improvement in the proposed model. The bid price similarity increases, and the eCPM increase rate of the proposed model decreases. If different ad networks do not consider users in an identical matter, the potential for type 1 and type 2 errors increases. However, a loss can be reduced by dividing sections in the proposed model and searching for ad networks that provide a higher bid price in each price section, which is deemed effective.

Table 22(a). Sensitivity analysis results

(a) When two demand curves have no intersection

eCPM Increase (%) (proposed vs. historical average)		Top N(%) Users for Ad Network 2										
		10%	**20%**	**30%**	**40%**	**50%**	**60%**	**70%**	**80%**	**90%**	**100%**	**AVG**
Bid Price Similarity (correlation coefficient)	**0**	*14.0%*	*7.56%*	*4.91%*	*3.69%*	*3.14%*	*2.44%*	*2.19%*	*1.94%*	*1.68%*	*1.51%*	4.31%
	0.1	*11.2%*	*6.34%*	*4.37%*	*3.33%*	*2.74%*	*2.22%*	*1.83%*	*1.63%*	*1.47%*	*1.34%*	3.64%
	0.2	*9.19%*	*5.33%*	*3.95%*	*2.89%*	*2.45%*	*1.88%*	*1.54%*	*1.54%*	*1.40%*	*1.20%*	3.14%
	0.3	*7.43%*	*4.35%*	*3.12%*	*2.35%*	*2.04%*	*1.63%*	*1.46%*	*1.26%*	*1.14%*	*1.08%*	2.59%
	0.4	*5.97%*	*3.52%*	*2.60%*	*1.99%*	*1.63%*	*1.34%*	*1.27%*	*1.02%*	*0.96%*	*0.90%*	2.12%
	0.5	*4.59%*	*2.82%*	*2.10%*	*1.59%*	*1.39%*	*1.13%*	*0.97%*	*0.88%*	*0.81%*	*0.73%*	1.70%
	0.6	*3.55%*	*2.16%*	*1.55%*	*1.22%*	*1.09%*	*0.84%*	*0.77%*	*0.71%*	*0.63%*	*0.59%*	1.31%
	0.7	*2.39%*	*1.48%*	*1.11%*	*0.88%*	*0.76%*	*0.62%*	*0.48%*	*0.54%*	*0.51%*	*0.47%*	0.92%
	0.8	*1.54%*	*1.00%*	*0.71%*	*0.59%*	*0.50%*	*0.37%*	*0.41%*	*0.33%*	*0.31%*	*0.33%*	0.61%
	0.9	*0.76%*	*0.47%*	*0.35%*	*0.30%*	*0.24%*	*0.19%*	*0.16%*	*0.19%*	*0.21%*	*0.15%*	0.30%
	1.0	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	0.00%
	AVG	5.52%	3.18%	2.25%	1.71%	1.45%	1.15%	1.01%	0.91%	0.82%	**0.75%**	1.88%

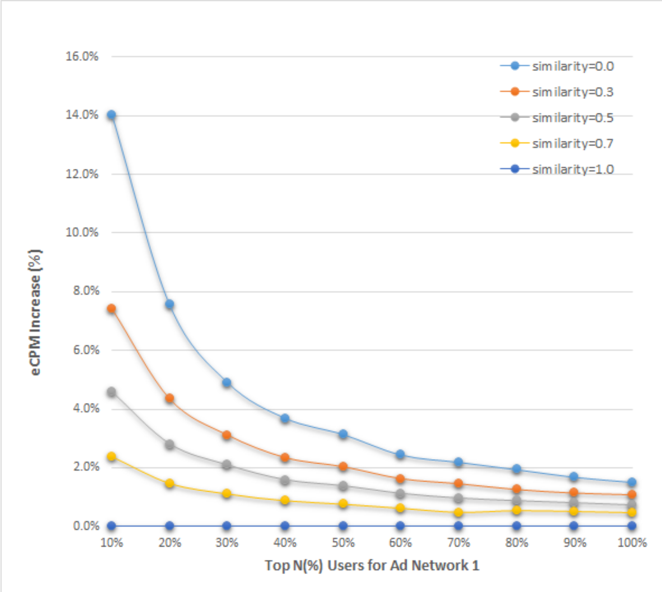
Table 22(b). Sensitivity analysis results

(b) When two demand curves have a cross point

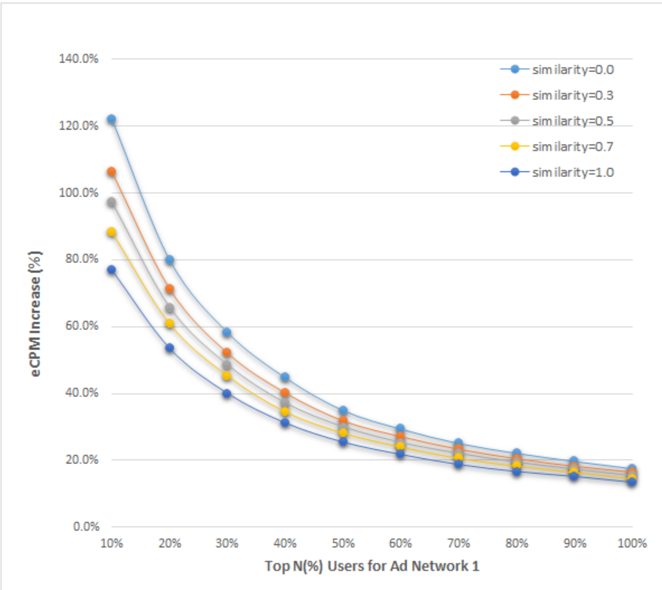
eCPM Increase (%) (proposed vs. historical average)		Top N(%) Users for Ad Network 1										
		10%	20%	30%	40%	50%	60%	70%	80%	90%	100%	AVG
Bid Price Similarity (correlation coefficient)	0	*122.0%*	*79.9%*	*58.3%*	*44.8%*	*35.0%*	*29.4%*	*25.2%*	*22.2%*	*19.8%*	*17.6%*	45.4%
	0.1	*116.5%*	*77.3%*	*56.5%*	*43.0%*	*34.1%*	*28.7%*	*24.6%*	*21.5%*	*19.4%*	*16.9%*	43.8%
	0.2	*111.2%*	*73.8%*	*54.4%*	*41.1%*	*33.2%*	*28.0%*	*24.3%*	*20.9%*	*18.8%*	*16.7%*	42.2%
	0.3	*106.4%*	*71.3%*	*52.1%*	*40.2%*	*31.9%*	*27.1%*	*23.4%*	*20.5%*	*18.3%*	*16.5%*	40.8%
	0.4	*101.1%*	*68.6%*	*50.4%*	*38.5%*	*31.5%*	*26.3%*	*22.6%*	*19.8%*	*17.8%*	*16.0%*	39.3%
	0.5	*97.2%*	*65.7%*	*48.5%*	*37.2%*	*30.0%*	*25.3%*	*22.1%*	*19.5%*	*17.4%*	*15.4%*	37.8%
	0.6	*92.8%*	*63.1%*	*46.7%*	*35.9%*	*29.0%*	*25.0%*	*21.6%*	*19.2%*	*16.8%*	*15.0%*	36.5%
	0.7	*88.3%*	*60.8%*	*45.3%*	*34.6%*	*28.2%*	*24.0%*	*20.7%*	*18.3%*	*16.5%*	*14.6%*	35.1%
	0.8	*84.0%*	*58.2%*	*43.3%*	*33.2%*	*27.2%*	*23.1%*	*20.5%*	*17.4%*	*16.2%*	*14.1%*	33.7%
	0.9	*80.8%*	*55.8%*	*41.8%*	*32.2%*	*26.5%*	*22.3%*	*19.3%*	*17.1%*	*15.5%*	*13.8%*	32.5%
	1.0	*76.9%*	*53.4%*	*40.0%*	*31.2%*	*25.4%*	*21.7%*	*18.7%*	*16.6%*	*15.2%*	*13.4%*	31.3%
	AVG	97.9%	66.2%	48.8%	37.4%	30.2%	25.6%	22.1%	19.4%	17.4%	**15.5%**	38.0%

Next, for each bid price similarity value between the two ad networks, the top N% value was set at 100%, 90%, 80%, …, and 10%. For each bid price similarity setting, the top N% sensitivity analysis were conducted using only the top N% users, where the bid price was higher than that of ad network 1 for Table 22(b) and 2 for Table 22(a). Similarly, each parameter of sensitivity analysis can be summarized, as in Table 22. When compared with N=100%, the performance of the proposed model apparently improved significantly the closer it came to the top 10%, where selling could be made at a higher price to ad network 1. The results are as follows: First, regardless of the bid price similarity, as N became smaller, eCPM improvement increased significantly. Second, the bid price similarity became closer to 0, rather than 1, (i.e., independent to each other), because of the higher possibility of reducing loss when selling the advertisement place to ad network 2, instead of 1.

Figure 20 depicts that the graph of eCPM increase rate observed as the top N% changed by 10% for the respective similarity parameters (e.g., 0.0, 0.3, 0.5, 0.7, and 1.0). Here, the smaller the top N (%) value, the greater the loss with the reverse waterfall bidding order for types (a) and (b). Therefore, in the proposed model, advertising revenue increased owing to loss reduction.



(a) When two demand curves have no intersection



(b) When two demand curves have a cross point

Figure 20. eCPM rate increase for different bid price similarity parameters

Chapter 5. Conclusion

5.1 Summary of Research Findings

This study focuses on two key challenges to maximize advertising revenue for mobile publishers: 1) advertising UX design and 2) the waterfall bidding strategy. It analyzes the empirical data and academic methodology and presents guidelines for mobile publishers.

First, the influence of various advertising factors on revenue (eCPM) and effectiveness (CTR) for advertising UX design were examined. In addition to various advertising factors reviewed by previous studies, new advertising factors that characterize the mobile environment and new ad formats such as native ad and rewarded video ads, which have been relatively recently introduced, were defined, and the influence on advertising revenue and effectiveness was examined. Then, guidelines that can be used when mobile publishers plan to add advertising to their services were presented.

First, as advertisement density increased, advertising revenue and effectiveness increased, and each increase rate was similar. Mobile publishers can earn reasonable advertising revenue as they assign to the advertising area. However, even when advertisement density was similar, differences were noted in advertising revenue and effectiveness between ad formats. Mobile publishers earned more using native banner ads in advertisement design with low advertisement density and rewarded video ads in advertisement design with high advertisement density, which is more helpful, in terms of advertising revenue.

Moreover, advertising revenue and advertising effectiveness appeared differently, depending on disclosure position, even though advertisement density was similar. Related research shows a high probability of the user noticing advertisements at the top of the screen; however, there is a high probability of the user clicking advertisements at the bottom of the screen. Lastly, with similar advertisement density, advertising revenue and effectiveness were different, depending on disclosure method. Although three types of disclosure method, namely, “Separated area,” “List UI,” and “Pop-up” can be expressed as native ads, “Pop-up” showed the highest advertising revenue and effectiveness.

Once mobile publishers decide on advertisement placement and ad format to add to their services using guidelines examining advertising revenue and effectiveness according to different factors, they require other guidelines to manage the waterfall strategy of setting and operating ad networks for each advertisement placement. This study proposed a method of estimating an appropriate reserve price based on the past transaction history of each ad network.

This study also provided dynamic reserve pricing strategies for each situation mobile publishers encounter when attempting to monetize mobile service traffic for a small number of multiple ad networks. First, the current study increases the possibility of selling advertisement inventory at a higher price by utilizing past data to select those with the highest bid price among multiple ad networks. Next, when sending advertisement requests to the same ad network, sequentially requesting multiple reserve prices enables the advertisement inventory to be sold at a higher price.

The sensitivity analysis empirically showed that a demand curve-based waterfall bidding strategy increases the mobile publisher's revenue. Specifically, using the reserve pricing method based on historical averages showed that (a) when two demand curves have no intersection, the level of improvement was 0.75%; (b) when two demand curves have an intersection, eCPM improved by an average of about 15.5% (see Table 22). In situations such as (b), the advertisement request is sold at a lower price, and loss occurs more frequently owing to the proposed demand curve-based waterfall bidding strategy, which has a greater effect in reducing this amount.

Moreover, the sensitivity analysis demonstrated that advertising revenue performance through the proposed demand curve-based bidding strategy enables publishers to improve advertising revenue noticeably when the bid price difference among networks is large (although determining when the situation may arise is difficult due to information asymmetry), and the correlation of bid prices proposed by the two networks (bid price similarity or correlation coefficient) is low (i.e., independent of each other).

5.2 Contribution of this Study

This study contributes in the following ways. First, it examines the effects of various advertising factors on revenue (eCPM) and effectiveness (CTR) for advertising UX design. In addition to various advertising factors examined by previous studies, this study defines new advertising factors that exist in mobile environments and new ad formats such as native ads and rewarded video ads to analyze the influence of factors on revenue and advertising effectiveness. This study suggested guidelines for maximizing advertising revenue when mobile publishers wish to add advertising to their services.

For practitioners, the proposed model theoretically shows that revenue performance in waterfall bidding can be improved if the eCPM distribution is predicted based on past transaction history. It also empirically proves that demand curve fitting is available and allows publishers to employ a sensitivity analysis for situations in which observations are not feasible, due to information asymmetry. The present study proposed a specific strategy for the publisher who adopts ad networks such as Google AdMob and Facebook Audience Network to monetize advertisements effectively using ad networks through this systematic approach. This study contributes to academia by proposing a new operation method for waterfall bidding optimization, a relatively less studied area in terms of optimization, compared with header bidding (or real-time bidding in advertising exchange platforms).

This study enhances the understanding of mobile advertising by providing standardized knowledge that is unknown to numerous mobile publishers without access to a separate R&D department related to advertising, using multiple ad networks in a real business environment. It provides an effective way to display advertisements optimized for mobile publishers and increase advertising revenue.

5.3 Limitation and Further Studies

This study has several limitations. In the analysis that discloses the influence between advertising factors and revenue and advertising factors and effectiveness, the data of each ad format and factor do not come from a single mobile app. Obtaining data that fit the designed experiment was very difficult because the mobile apps used to collect data for this study are actually still running services. Therefore, the advertisement data used in this study should combine the data of ad formats and factors from various mobile apps. On the one hand, actually operating data has advantages, but it has the disadvantage of limiting data collection and processing that would increase the completeness of the experimental design due to observational data.

The sensitivity analysis results are neither tested nor proven in actual settings against the proposed model. Thus, a field experiment must be conducted in the future with the condition that one bidding side uses the historical average method set as the control group, and the other side conducts the demand curve-based bidding strategy set as the treatment group. Follow-up studies are planned to verify whether the test results follow the results of sensitivity analysis proposed by this research. Moreover, the alpha and beta values of the demand curves set through the process of sensitivity analysis represent only a specific situation and do not explain generalized situations. Thus, the algorithm should be generalized in a further study to test the model’s robustness.

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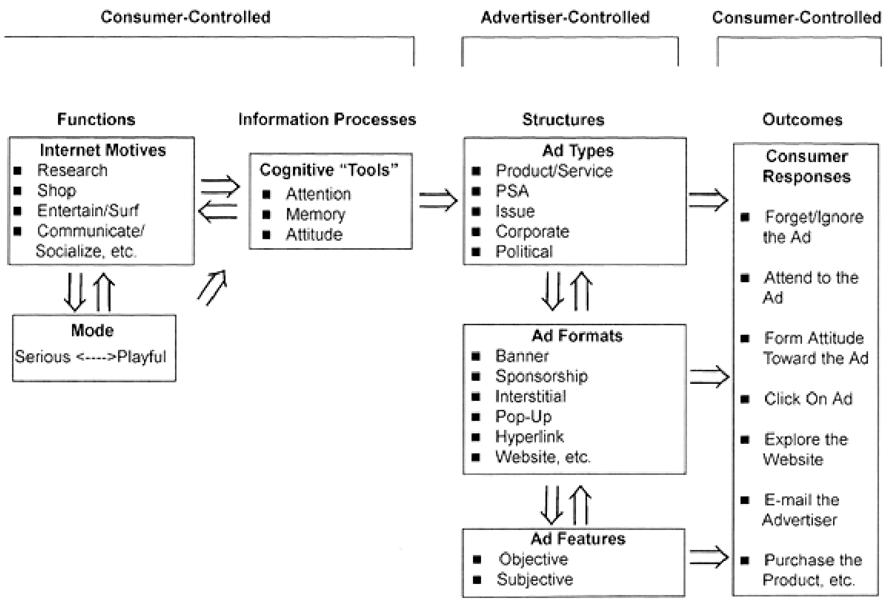
Appendix

1. Frameworks describing the relationship between ad factors and advertising effectiveness

1.1. Interactive Advertising Model (Rodgers and Thorson, 2000)

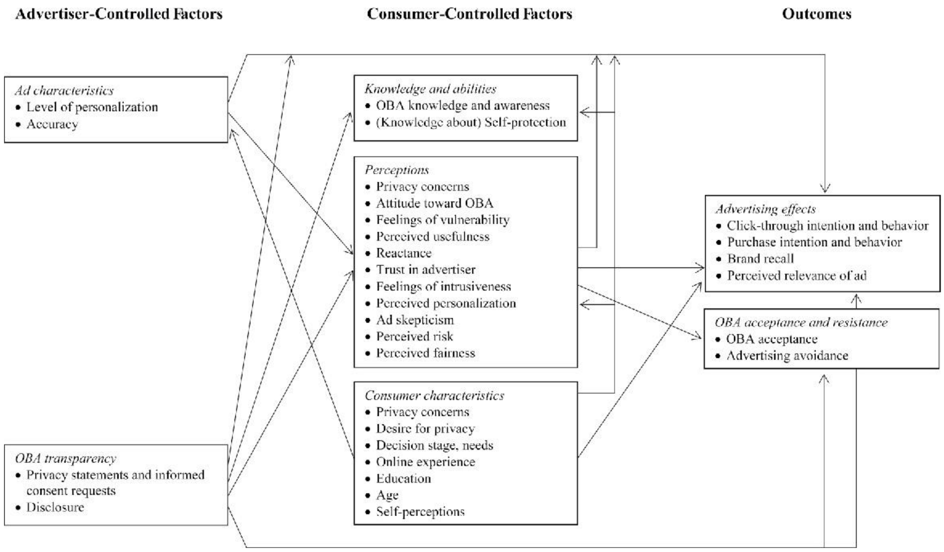
This model proposes an interactive information processing model of internet advertising that incorporates both function and structure. Although past advertising models have accounted for processing in a broadcast and/or print medium, they do not include aspects unique to the internet namely, interactivity and virtual reality. This model assumes that the individual is an active initiator and participator in the online experience (see Hoffman and Novak, 1996). Moreover, the assumptions of functionalism provide a rationale for structuring the interactive advertising model (IAM), beginning with motives and followed by information processes.



Interactive Advertising Model (Rodgers and Thorson, 2000)

1.2. Online Behavioral Advertising (Boerman et al,, 2017)

Online behavioral advertising (OBA) is defined as the practice of monitoring people's online behavior and using the collected information to show them individually targeted advertisements. This model first identified all variables that were studied with respect to OBA and grouped them into three main factors based on the interactive advertising model (Rodgers and Thorson 2000). This model explains how consumers perceive and process online ads and distinguishes three main types of factors: advertiser-controlled factors, consumer-controlled factors, and advertising outcomes.

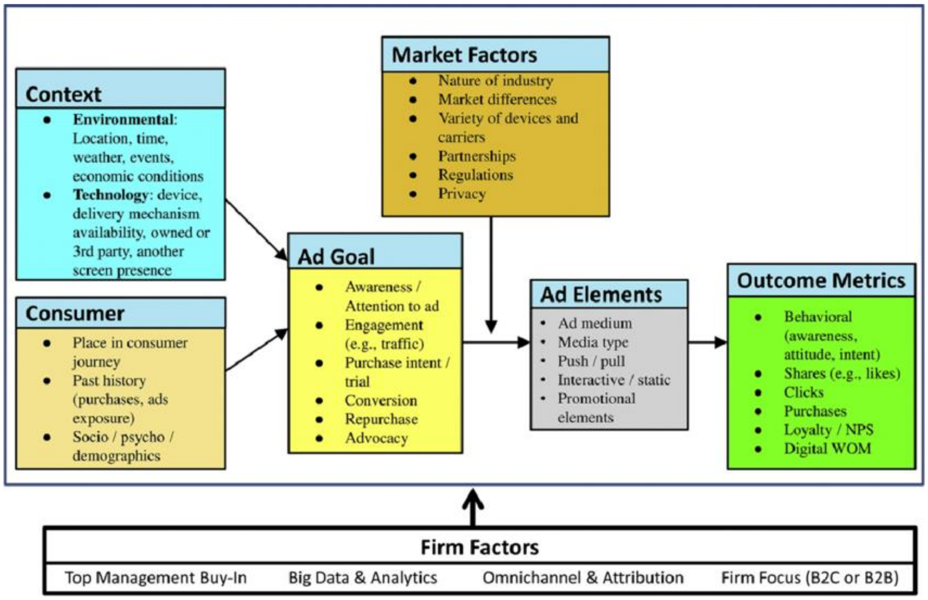


Online Behavioral Advertising (Boerman et al,, 2017)

1.3. Mobile Advertising Effectiveness Framework (Grewal et al., 2016)

This model develops and presents a mobile advertising effective -ness framework, which comprises environmental and technological context factors, advertising goals that match the consumer's location in the shopping decision-making journey, market factors, ad elements, and outcome metrics.

This framework has seven main components. Especially contextual components are considered such as environmental context and technological context, consumer-related contextual variables, market factors, and firm-level macro factors.

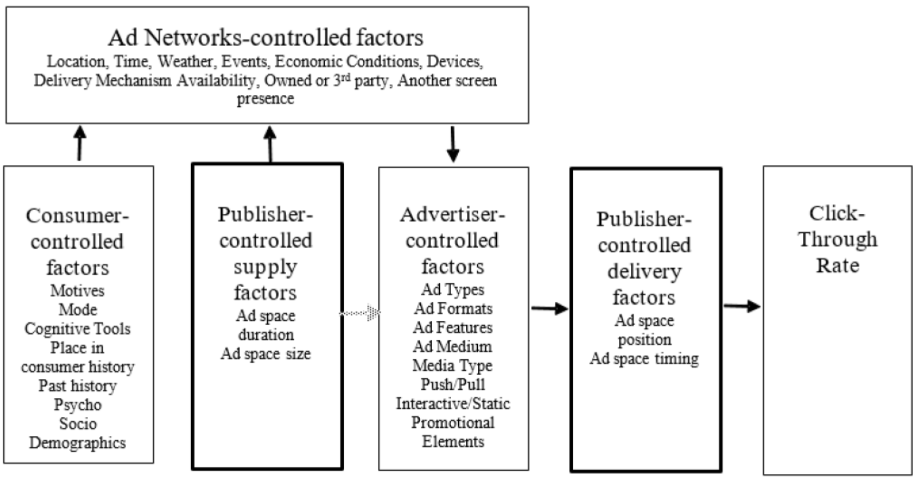


Mobile Advertising Effectiveness Framework (Grewal et al., 2016)

1.4. Integrated Mobile In-App Effectiveness Framework (Truong et al., 2019)

This model conceptualizes the role of publishers and proposes an integrated effectiveness framework to improve the effectiveness of mobile in-app advertising for all participants involved. Two new components of factors introduced with the framework are publishers and ad networks.

The common outcome metric is the click-through rate, which measures the short-term and long-term goals of all participants. The framework is structured based on how ads are served from the consumer request until completion. It also reflects the relationships between publishers and other participants by aligning the achievement of common goals.



Integrated Mobile In-App Effectiveness Framework (Truong et al., 2019)

2. Descriptive features of ad units of dataset

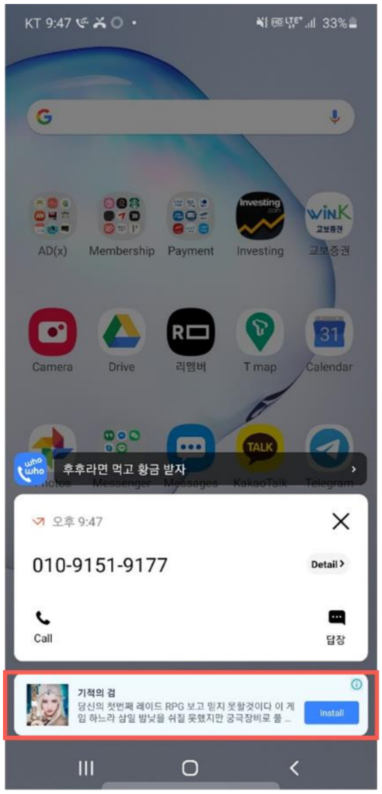
Mobile App	Ad Format	Ad density	Size	Disclosure Position	Disclosure Method
WhaleShooter	Banner ad	5.8%	320x30	Top	Separated area
Strikers 1999	Banner ad	5.8%	320x30	Top	Separated area
Flower Witch Match3	Banner ad	5.8%	320x30	Top	Separated area
Wild Tamer	Banner ad	5.8%	320x30	Top	Separated area
Baseball Live	Banner ad	5.8%	320x30	Bottom	Separated area
Metroid HD	Banner ad	5.8%	320x30	Bottom	Separated area
Subway Korea	Banner ad	5.8%	320x30	Bottom	Separated area
Subway Korea	Native banner ad	15.8%	320x50	Middle	List UI
Whowho	Native banner ad	8.0%	320x40	Bottom	Pop-up
스마트택배	Native banner ad	12.9%	320x60	Middle	List UI
전국 스마트 버스	Native banner ad	12.9%	320x60	Middle	List UI
전국 스마트 버스	Native banner ad	5.8%	320x30	Bottom	Separated area
1km	Native ad	22.8%	320x110	Middle	List UI
CandyCamera	Native ad	27.3%	320x130	Top	Separated area
MEEFF	Native ad	24.2%	320x120	Top	Separated area
Mobizen Screen Recorder	Native ad	47.1%	320x225	Bottom	Pop-up
Mobizen Screen Recorder	Native ad	19.7%	235x130	Middle	Pop-up
MEEFF	Native interstitial ad	100.0%	320x480	Full Screen	Pop-up
1km	Native interstitial ad	100.0%	320x480	Full Screen	Pop-up
Pikicast	Native interstitial ad	100.0%	320x480	Full Screen	Pop-up
Mad Runner	Interstitial ad	100.0%	320x480	Full Screen	Pop-up
Mad Runner	Rewarded video ad	100.0%	320x480	Full Screen	Pop-up
Strikers 1999	Interstitial ad	100.0%	320x480	Full Screen	Pop-up
Strikers 1999	Rewarded video ad	100.0%	320x480	Full Screen	Pop-up
My Oasis	Interstitial ad	100.0%	320x480	Full Screen	Pop-up
My Oasis	Rewarded video ad	100.0%	320x480	Full Screen	Pop-up

- Data of “Violet” was used to verify H1.
- Data of “Green” was used to verify H2.a.
- Data of “Yellow” was used to verify H2.b.

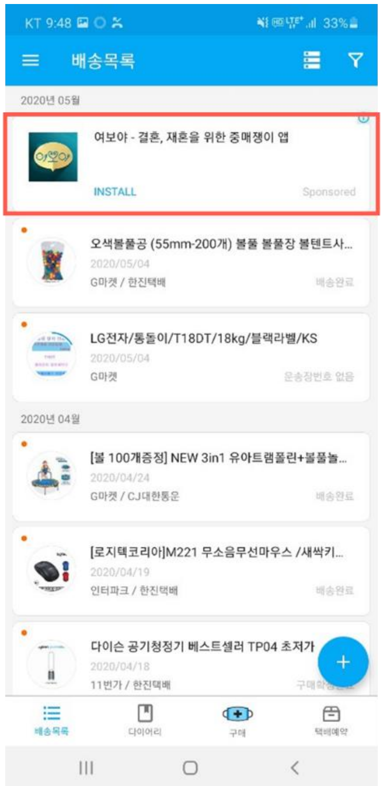
- Data of “Orange” was used to verify H3.
- Data of “Blue” was used to verify H4.

3. Screenshots of ad units of dataset

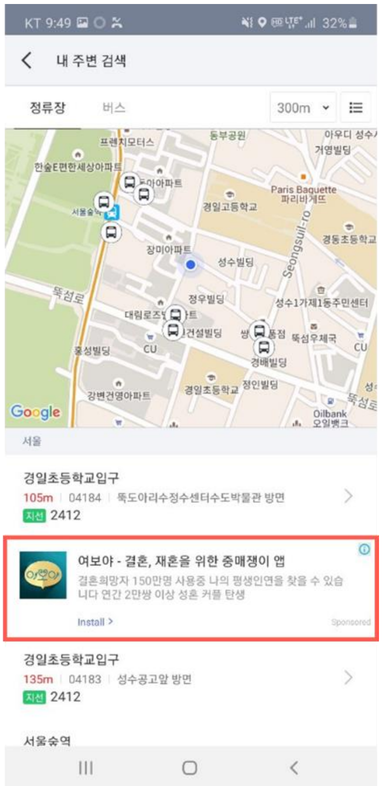
3.1. Screenshots of native banner ads



whowho

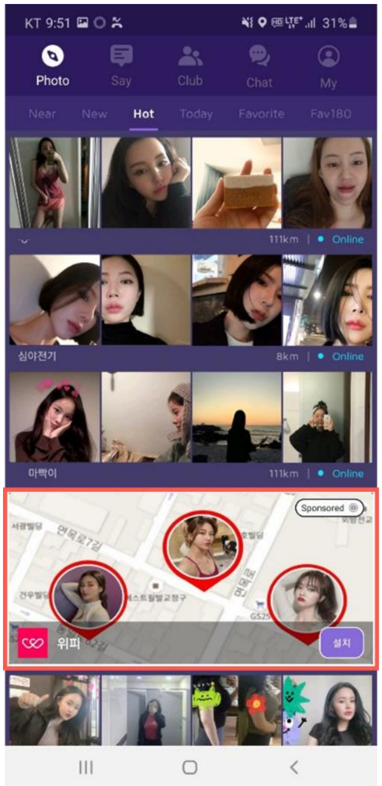


스마트택배

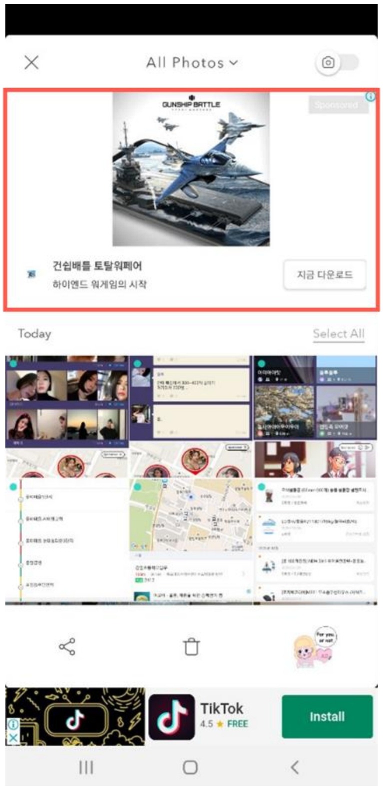


전국 스마트 버스

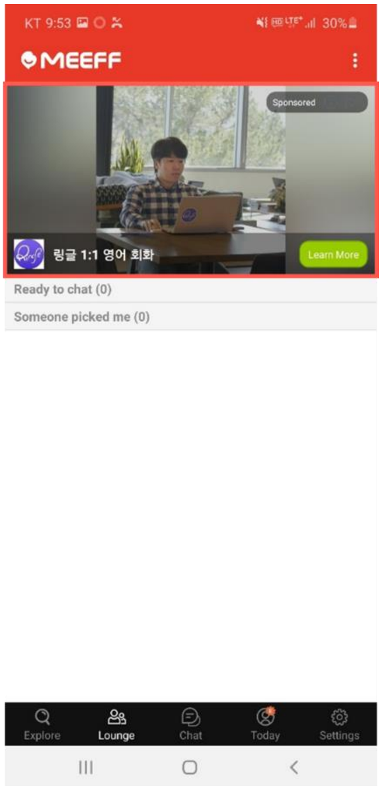
3.2. Screenshots of native ads



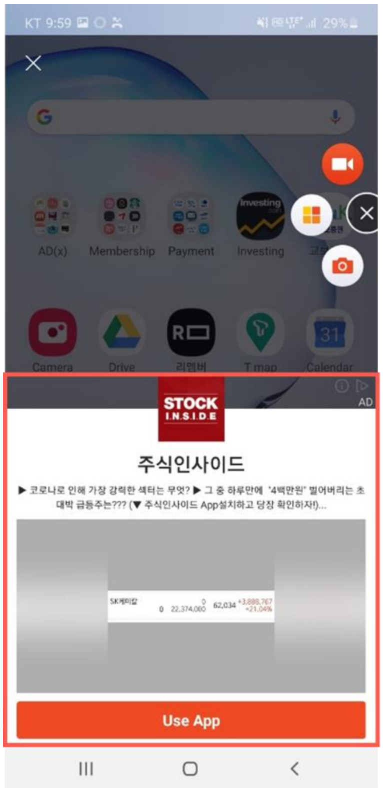
1km



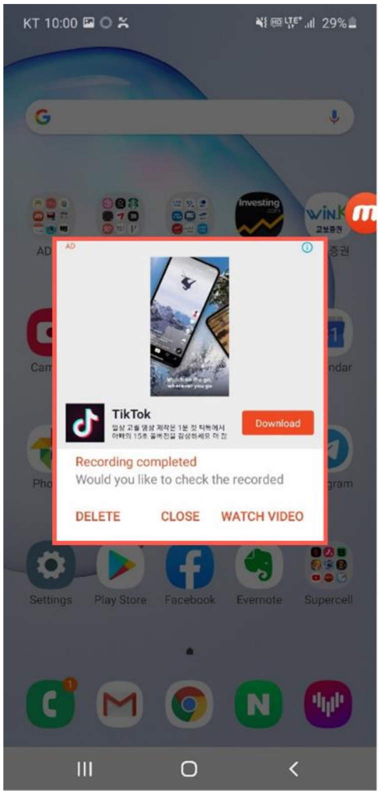
Candy Camera



Meeff



Mobizen Screen Recorder



Mobizen Screen Recorder

4. Components of dataset

date	app	adName	osType	mediationType	adNetwork	request	fill	impression	click	revenue	ecpm	fillrate	showrate	ctr	priceFloor
2019-01-01	스마트택배	Native Ad	android	mopub	Total	369014	173297	84772	1503	265.3714624	3.13	46.96	48.91	1.77	N/A
2019-01-01	스마트택배	Native Ad	android	mopub	adexchange	210814	93083	39233	707	175.19	4.465373538	44.15408844	42.14840519	1.802054393	4.49
2019-01-01	스마트택배	Native Ad	android	mopub	admob	50609	47032	12357	149	24.69	1.998057781	92.93208718	26.27360095	1.205794287	0.59
2019-01-01	스마트택배	Native Ad	android	mopub	mopub	107591	33182	33182	647	65.49146239	1.97370449	30.84086959	100	1.94985233	N/A
2019-01-01	스마트택배	Native Ad	iphone	mopub	Total	232551	84808	61708	282	42.14835481	0.68	36.46	72.76	0.45	N/A
2019-01-01	스마트택배	Native Ad	iphone	mopub	facebook	64499	45893	22793	45	9.075103712	0.398153105	71.15304113	49.66552633	0.197429035	188.38
2019-01-01	스마트택배	Native Ad	iphone	mopub	mopub	168052	38915	38915	237	33.0732511	0.849884392	23.15652298	100	0.609019658	N/A
2019-01-02	스마트택배	Native Ad	android	mopub	Total	840369	407737	232351	3612	633.1773077	2.72	48.51	56.98	1.55	N/A
2019-01-02	스마트택배	Native Ad	android	mopub	adexchange	374984	183605	85364	1356	407.19	4.770043578	48.96342244	46.49328722	1.588491636	3.89
2019-01-02	스마트택배	Native Ad	android	mopub	admob	102140	99620	22475	280	30.22	1.344605117	97.53279812	22.56073078	1.245828699	0.64
2019-01-02	스마트택배	Native Ad	android	mopub	mopub	363245	124512	124512	1976	195.7673077	1.57227663	34.27769137	100	1.586995631	N/A
2019-01-02	스마트택배	Native Ad	iphone	mopub	Total	736916	253234	191824	750	124.2053746	0.64	34.36	75.74	0.39	N/A
2019-01-02	스마트택배	Native Ad	iphone	mopub	facebook	156541	118732	57322	163	21.65126769	0.377713054	75.84722213	48.2784759	0.284358536	188.38
2019-01-02	스마트택배	Native Ad	iphone	mopub	mopub	580375	134502	134502	587	102.5541069	0.762472728	23.17501615	100	0.436424737	N/A
2019-01-03	스마트택배	Native Ad	android	mopub	Total	811834	350109	237066	3501	653.1586347	2.75	43.12	67.71	1.47	N/A
2019-01-03	스마트택배	Native Ad	android	mopub	adexchange	330528	142684	80288	1646	379.5	4.726733759	43.16850615	56.269799	2.05011957	3.76
2019-01-03	스마트택배	Native Ad	android	mopub	admob	85677	84069	33422	345	41.39	1.238405841	98.12318358	39.75543898	1.032254204	0.59
2019-01-03	스마트택배	Native Ad	iphone	mopub	Total	783771	260935	211801	884	145.0040658	0.68	33.29	81.17	0.41	N/A
2019-01-03	스마트택배	Native Ad	android	mopub	mopub	395629	123356	123356	1510	232.2686347	1.882913152	31.17971635	100	1.224099355	N/A
2019-01-03	스마트택배	Native Ad	iphone	mopub	facebook	125548	93771	44637	113	19.6399593	0.439992815	74.68936184	47.60213712	0.253153214	178.46
2019-01-03	스마트택배	Native Ad	iphone	mopub	mopub	658223	167164	167164	771	125.3641065	0.749946798	25.39625628	100	0.461223709	N/A
2019-01-04	스마트택배	Native Ad	android	mopub	Total	732474	311626	178726	2247	466.7926679	2.61	42.54	57.35	1.25	N/A
2019-01-04	스마트택배	Native Ad	android	mopub	adexchange	278796	101698	50300	785	244.37	4.858250497	36.47756783	49.46016638	1.560636183	3.89
2019-01-04	스마트택배	Native Ad	iphone	mopub	mopub	540773	177548	177548	713	138.0434447	0.777499294	32.83226049	100	0.401581544	N/A
2019-01-04	스마트택배	Native Ad	android	mopub	admob	111386	109474	27972	143	21.66	0.774345774	98.28344675	25.55127245	0.511225511	0.66
2019-01-04	스마트택배	Native Ad	android	mopub	mopub	342292	100454	100454	1319	200.7626679	1.998553248	29.34745773	100	1.313038804	N/A
2019-01-04	스마트택배	Native Ad	iphone	mopub	Total	608119	224940	199771	760	146.687145	0.73	36.98	88.81	0.38	N/A
2019-01-04	스마트택배	Native Ad	iphone	mopub	facebook	67346	47392	22223	47	8.643700332	0.388952902	70.37092032	46.89188049	0.211492598	188.38
2019-01-05	스마트택배	Native Ad	android	mopub	Total	298829	103735	71558	1053	169.1092073	2.36	34.71	68.98	1.47	N/A
2019-01-05	스마트택배	Native Ad	iphone	mopub	Total	256949	98713	95472	477	83.39868527	0.87	38.41	96.71	0.49	N/A
2019-01-05	스마트택배	Native Ad	iphone	mopub	facebook	10667	6288	3047	11	1.257950098	0.412848736	58.94815787	48.45737913	0.36101083	188.38
2019-01-05	스마트택배	Native Ad	iphone	mopub	mopub	246282	92425	92425	466	82.14073518	0.888728539	37.52811817	100	0.504192589	N/A
2019-01-05	스마트택배	Native Ad	android	mopub	adexchange	75788	25338	13651	269	67.4	4.937367226	33.43273341	53.87560186	1.970551608	3.82
2019-01-05	스마트택배	Native Ad	android	mopub	admob	27860	25746	5256	30	4.53	0.861872146	92.4120603	20.41482172	0.570776256	0.56
2019-01-05	스마트택배	Native Ad	android	mopub	mopub	195181	52651	52651	754	97.17920731	1.845723867	26.97547405	100	1.432071566	N/A
2019-01-06	스마트택배	Native Ad	android	mopub	admob	46364	31770	14920	85	9.37	0.628016086	68.52299198	46.96254328	0.569705094	0.49
2019-01-06	스마트택배	Native Ad	iphone	mopub	Total	119662	48153	40246	224	36.74152444	0.91	40.24	83.57	0.55	N/A
2019-01-06	스마트택배	Native Ad	android	mopub	Total	271490	108113	64445	982	206.6626262	3.2	39.82	59.6	1.52	N/A
2019-01-06	스마트택배	Native Ad	iphone	mopub	facebook	25062	15621	7714	13	2.615372852	0.339042371	62.32942303	49.38224185	0.16852476	188.38
2019-01-06	스마트택배	Native Ad	iphone	mopub	mopub	94600	32532	32532	211	34.12615159	1.04900257	34.38900634	100	0.648592155	N/A

5. Log-level model

$$\ln(y) = \beta_0 + \beta_1 x$$

$$\exp(\ln(y)) = \exp(\beta_0 + \beta_1 x)$$

$$y = \exp(\beta_0 + \beta_1 x)$$

Therefore, a log-transformed dependent variable implies that simple linear model has been exponentiated. Considering the product rule of exponents, it can be written the last line above as

$$y = \exp(\beta_0)\exp(\beta_1 x)$$

This further implies that the independent variable has a multiplicative relationship with the dependent variable instead of the usual additive relationship. Hence the need to express the effect of a one-unit change in x on y as a percent.

Abstract (Korean)

광고 수익은 모바일 매체에게 있어서, 인앱 판매 (in-app purchase) 와 함께 중요한 수익원 중 하나가 되었다. 본 연구에서는 모바일 매체가 광고 수익을 최대화하고자 할 때 마주하게 되는 두 가지 핵심 과제를 실증적인 데이터와 학술적인 방법론을 통해 해결하고자 하였다.

본 연구는, Google AdMob, Facebook Audience Network 를 포함하는 다수의 광고 네트워크를 동시에 운영하여 모바일 매체의 광고 수익을 최적화하는 서비스를 제공하고 있는 기업, 주식회사 애드엑스의 2019년 광고 결과 통계 데이터에서 추출하여 분석과 평가를 진행하였다.

모바일 매체가 광고를 통해 수익을 얻고자 할 때 가장 처음으로 마주하는 과제는, 모바일 매체의 서비스 UX에 최적화된 광고 위치와 광고 포맷을 결정하는 것이다. 이 결정에 가이드라인을 제공하기 위해, 상대적으로 최근 도입된 네이티브 광고, 리워드 비디오 광고를 포함한 모바일 광고가 가지는 특징을 분석하였다. 그 결과, 전통적인 광고 매체에 노출되는 광고를 통해 정의된 다양한 광고 요소 외에, 세 가지 신규 광고 요소; 광고 밀도, 노출 위치, 노출 방법을 정리하였으며, 도출된 신규 광고 요소와 광고 수익, 광고 효과 간의 관계를 분석하였다.

먼저, 서비스 화면 내에 광고가 차지하는 비율인 광고 밀도와 관련하여, 광고 밀도가 높을수록 광고 수익과 광고 효과, 모두 높은 결과를 얻었다. 한편, 유사한 광고 밀도를 가진 광고 간에도 광고 포맷에 따라 광고 수익, 광고 효과가 차이를 보였다. 낮은 광고 밀도를 가진 광고 중에서는 네이티브 배너 광고가 배너 광고 보다 더 높은 광고 수익과 광고 효과를 보였으며, 높은 광고 밀도를 가진 광고 중에서는 리워드 비디오 광고가 가장 높은 광고 수익을 나타냈고, 전면 광고가 가장 높은 광고 효과를 보였다.

두번째 신규 광고 요소인 노출 위치와 관련하여, 기존 PC 또는 웹 환경에서는 화면 상단에 노출된 광고의 광고 효과가 가장 높았으나, 모바일 환경에서는 화면 아래에 노출된 광고가 광고 수익, 광고 효과, 모두 더 높게 나타났다.

마지막으로, 노출 방법 와 관련한 분석에서는, 동일한 네이티브 광고 포맷이지만, 모바일 매체에 의해 개발된 노출 방법에 따라, “분리된 영역”, “리스트 UI”, “Pop-up” 로 구분하였고, 다양한 노출 방법에 따른 광고 수익, 광고 효과를 비교 분석해 보았다. 그 결과 “Pop-up” 형태의 노출 방법에서 가장 높은 광고 수익과 광고 효과가 나타났다.

모바일 매체가 광고 위치와 광고 포맷을 결정한 뒤에 직면하는 두번째 핵심 과제는, 다수의 광고 네트워크로부터 광고를 제공받아 노출할 때, 광고 수익이 최대화 될 수 있도록 각 광

고 네트워크의 우선순위, 예약 가격 (reserve price) 등 워터폴 세팅을 최적화 하는 것이다. 한편, 광고 네트워크와 모바일 매체 사이에는 광고 네트워크가 더 많은 정보를 가지고 있는 정보 비대칭이 존재하는데, 본 연구는 이런 정보 비대칭 하에서 광고 수익을 최대화 위하여, 최저 가격 (reserve price) 전략을 통한 워터폴 세팅 방법을 제안하였다.

먼저, 모바일 매체의 광고 판매 가격이 최적화 되어 있는지를 설명하기 위하여 수요 곡선 기반 모델을 설계하였다. 그리고, 민감도 분석을 통해 제안된 모델이 기존 운영 전략보다 우수함을 비교해 보였다. 또한, 제안된 모델을 통해, 광고 네트워크 간의 입찰 가격이 상관 관계가 있을 때보다 독립적일 때 더 높은 광고 수익을 얻을 수 있음을 밝혔다.

본 연구를 통해, 학술적인 의미 뿐만 아니라, 실제 경영 환경에서 모바일 매체가 광고 수익을 창출하고 극대화하기 위해서 활용할 수 있는 가이드라인을 제공하였다. 특히 광고 네트워크에 대한 의존도가 높고, 내부 자원의 제약이 있는 중소 개발자들에게 별도의 R&D 없이 최적화된 광고 운영 정책을 수립할 수 있는 방법을 제시하였다.

주요어 : 디지털 마케팅, 모바일 매체, 광고 요소, 워터폴 입찰 전략, 광고 수익 최적화

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