Asia Pacific Journal of Information Systems
Vol. 25 No. 3 (SEPTEMBER 2015), 548-562

ISSN 2288-5404 (Print) / ISSN 2288-6818 (Online)
http://dx.doi.org/10.14329/apjis.2015.25.3.548

The Role of Application Rank in the Extended Mobile Application Download

Youngsok Bang[a], Dong-Joo Lee[b,*]

[a] *Assistant Professor, CUHK Business School, Chinese University of Hong Kong, Hong Kong*
[b] *Associate Professor, Division of Management, Hansung University, Korea*

A B S T R A C T

The growing popularity of mobile application has led to researchers and practitioners needing to understand users' mobile application download behaviors. Using large-scale transaction data obtained from a leading Korean telecommunications company, we empirically explore how application download rank, which appears to users when they decide to download a new application, affects their extended mobile application download. This terminology refers to downloading an additional application in the same category as those that they have already downloaded. We also consider IT characteristics, user characteristics, and application type that might be associated with the extended application download. The analysis generates the following result. Overall, a higher rank of a new application encourages the extended application download, but the linear relationship between the rank and the extended application download disappears when critical rank points are incorporated into the model. Further, no quadratic effect of rank is found in the extended application download. Based on the results, we suggest theoretical and managerial implications.

Keywords: Mbile Application, Extended Application Download, Application Rank, Large-Scale Data

Ⅰ. Introduction

The mobile application market has shown strong growth over the past years and this trend is expected to accelerate for the next decade. Statistics show that the number of applications available in each of the Apple App Store and Google Play is over 1.3 million as of September, 2014.[1] The growth of the mobile application market is largely driven by the progress of mobile Internet technology and the improvement of user interface of mobile devices. Enlarged bandwidth and advances in relevant encoding technology have made mobile application downloads faster and cheaper. With easy-to-use interface facilitating enhanced user experience, the penetration of new mobile devices is boosting the mobile application market as well.

Given that critical utility from mobile devices are

1) http://en.wikipedia.org/wiki/App_Store_(iOS); http://en.wikipedia. org/wiki/Google_Play

This work was supported by the National Research Foundation of Korea Grant funded by the Korean Government (NRF-2013S1A5B5A07049003) for Youngsok Bang and by Hansung University for Dong-Joo Lee.

*Corresponding Author. E-mail: djlee@hansung.ac.kr Tel: 8227605934

from the applications that users can choose and install (Han et al., 2013; Jung and Hong, 2014), understanding users' adoption of the applications is becoming essential for business players in the mobile application market such as network operators, application developers, application market-makers, and mobile marketers. Application download is a major revenue source for application developers and market-makers. Mobile marketers could also effectively build their customer base by making users download their applications (Vatanparast, 2009). Further, understanding user application download behavior could generate implications for network operators that provide users with access infrastructures and channels for the applications.

In this study, we empirically examine users' extended application download with a focus on the role of application rank. Extended application download refers to an additional application download in the category that they have already downloaded.[2)] For example, you could download a new mobile game, although you already have a mobile game installed in your mobile device. In this case, the new download would be an extended download. Each application download could be classified into either the initial download in an app category or an extended download in the category.

Mobile users are already using a variety of mobile applications across categories, and therefore, most of their new application downloads would be extended application downloads. Further, the extended application download might lead to the substitution of an application already installed in their mobile devices or the synergy between the existing and new applications. An additional game application download, for example, could reduce the playing time of the game application already installed, while the MS-Excel application download could bring a synergy with the MS-Word application. Therefore, understanding users' extended application download behaviors would be crucial for mobile application developers and marketers who are interested in the promotion of a new application or the usage of their current applications. Lastly, although extended downloads have not been the focus in previous ranking studies, extended downloads could be subject to distinctive ranking effects and might need to be differentiated from initial downloads as a user has already experienced downloading and using a popular application in the same category, which we will show later.

There are theoretical and methodological factors characterizing mobile application download unique from the case of software download to PC. First, it has been suggested that the mobile channel and the PC channel are different in their search capabilities because the mobile channel has a disadvantage in usability incurred by constraints in mobile devices (e.g., small screens) and mobile networks (e.g., low bandwidth) (Bang et al., 2013; Ghose et al., 2012; Zhang, 2007). Specifically, compared to the PC channel, the mobile channel offers a limited information search capability, which implies higher search costs and thus could affect choices of goods (Bang et al., 2013). In their empirical study of a microblogging site, Ghose et al. (2012) suggest that ranking effects are higher on mobile phones than on PCs by showing that messages near the top of the screen receive more clicks from users and this relationship is stronger for mobile users than PC users because of higher search costs. Their data and research context of microblogging involve content consumption without monetary transactions, which might limit the applic-

2) Mobile applications are classified into several categories by the app store, based on similarity in function or purpose of applications (e.g., game, location/traffic, etc.) and those categories are exposed to users.

ability of the result to mobile application downloads that entail transactions. Relatedly, ranking effects have been explored in sponsored search advertising on PCs, however, the empirical results are not consistent. Ghose and Yang (2009) explore sponsored search advertising data on Google and find that conversion rates, which involve transactions, are negatively related with rank. Thus, the rates are highest at the top and decrease with rank. However, another empirical study (Agarwal et al., 2011) on sponsored search advertising on Google shows that conversion rate increases with rank, a contradictory result to that of Ghose and Yang (2009). Therefore, the previous empirical studies do not provide definite predictions about ranking effects in the context of transactions over mobile channels. This study aims to fill the gap and contribute to this stream of literature by investigating the effect of application rank on extended mobile application download.

Second, while a PC is frequently shared with others (e.g., at home or at schools), mobile devices are more personal in its nature than PCs (Chae and Kim, 2003). This implies that a record of a mobile application download could be attributed to a specific user and mobile application download history could more vividly show individual preference and value system. Therefore, mobile application transaction data could provide objective and reliable information on the user's adoption of mobile applications, without the need to rely on a user survey as in the study of IT adoption in the PC context. However, previous studies on users' mobile application adoption behavior are usually based on survey data (e.g., Chung and Park, 2007; Oh, 2014). This study contributes to the literature on mobile application adoption by empirically exploring the role of application rank in the extended application download based on a large-scale transaction dataset from a major telecommunications company in Korea.

We employ a random-effects generalized least squares regression that considers not only application rank but also a variety of IT, user, and application characteristics. The analysis generates the following results. Overall, a higher rank of an application encourages the extended application download, but the linear relationship between the rank and the extended application download disappears when critical rank points are considered in the model. Further, there is no quadratic effect of rank found in the extended application download.

The rest of this paper is organized as follows. We discuss the role of rank in the extended application download in the following section. In subsequent sections, we describe our data and econometric model. Then, we analyze the model and present the analysis result. Finally, we conclude with a discussion about our findings and suggestions for future research.

Ⅱ. Mobile Application Rank and Extended Application Download

2.1. Effects of Application Rank on Extended Download

We conjecture, based on the rational choice theory, that mobile application users would make rational choices when deciding to do an extended download by calculating the cost and benefit involved in the download. Rational choice theory, which is rooted in utility theory in economics, is an approach used by social scientists to understand human decision-making. According to the rational choice theory, a person makes choices in a way to maximize the total utility within a given choice set and information.

The theory has been widely adopted in various disciplines, all-encompassing from economics, sociology, psychology, zoology, and political science to management, and explains human behaviors in a concise way (Green, 2002; Herrnstein, 1990).

Rational choice theory, coupled with the baseline assumptions that human wants more rather than less of a good and all the available resources are scarce in maximizing the utility, views any social exchange relationship such as firm-consumer relationship as an economic exchange relationship where all parties try to make cost-effective decisions. Therefore, mobile users would also follow the calculus of (expected) costs and benefits in the extended application download.

A mobile application user would download an application when s/he expects more benefit than the cost of downloading and using the application. Application popularity can be a positive quality signal (thus, a benefit signal) to consumers when downloading an application. Mobile application can be classified as an experience good in which qualities could not be determined prior to purchase (Nelson, 1974). Given that agreement with others decreases perceived uncertainty involved in decision making (McGarty et al., 1993) and that application download rank appears to users when they decide to download a new application, users would put more value on higher-ranked applications. Further, the user might expect gains from interacting with others, and thus, could choose an application having a larger customer base. From the above discussion, we could conjecture that a higher rank of an application would encourage the download of the application.

The effect of the application popularity on download can be interpreted as a herding effect as well. This herding effect is spotted in a variety of contexts such as financial investment (Grinblatt et al., 1995), information sharing (Avery and Chevalier, 1999; Oh and Jeon, 2007), product choice (Ge et al., 2009), political voting (Dekel and Piccione, 2000), software download (Duan et al., 2009), and IT adoption (Li, 2004). The primary explanation provided in the previous studies for the observation of herd behavior is information cascades (Banerjee, 1992; Bikhchandani et al., 1992). Informational cascades refer to the situation where it is optimal for an individual to follow the decision that the others have made while ignoring her own information. A rational consumer might be aware that the probability, if all are independent, of a majority of others making the wrong choice is small (Shiller, 1995). Therefore, the user might follow the decision that the majority has made, rather than pay for the costs of processing information to make a right choice, especially when a large amount of information is given to be processed.

Further, limited user interfaces of mobile devices such as small screens and inconvenient keypads incur high search costs to mobile users and might discourage them to search for low-ranked applications (Ghose et al., 2012), which are usually displayed in the second or next pages of search results. This leads to our second conjecture that there might be the critical values of ranks in terms of their effect on the mobile application download. For example, if ten applications are displayed in one page, then the effect of rank between the ninth and tenth applications may be different from that between the tenth and eleventh applications because moving to a different page may incur a higher cost than moving down in the same page.

While previous studies have suggested monotonic effects of rank (Agarwal et al., 2011; Ghose and Yang, 2009; Ghose et al., 2012), the effect of application rank becomes less obvious in the extended download. Given that users might already have downloaded high-ranked applications and the ranks are quite stable over time, the rank effect on the extended download might be different from the case of the initial download in the category. <Figure 1> depicts the total number of extended downloads per application rank during our data period. This roughly shows the extended download pattern in our dataset in terms of the relationship between the number of extended downloads and the rank at the time of the downloads.

First, as conjectured earlier, there is a global trend that higher ranks are associated with more downloads, but the highest ranked application was downloaded much less than the second highest ranked application (see A in <Figure 1>). That might be because the users could already have the highest ranked application installed in their mobile devices.

Second, several critical values of ranks in terms of their effect on the extended application download are spotted. Specifically, there are huge drops in the number of extended downloads at certain ranks (B, C, and D in <Figure 1>). The existence of critical values indirectly supports our second conjecture that mobile users could face huge search costs for downloading applications displayed in the next pages.

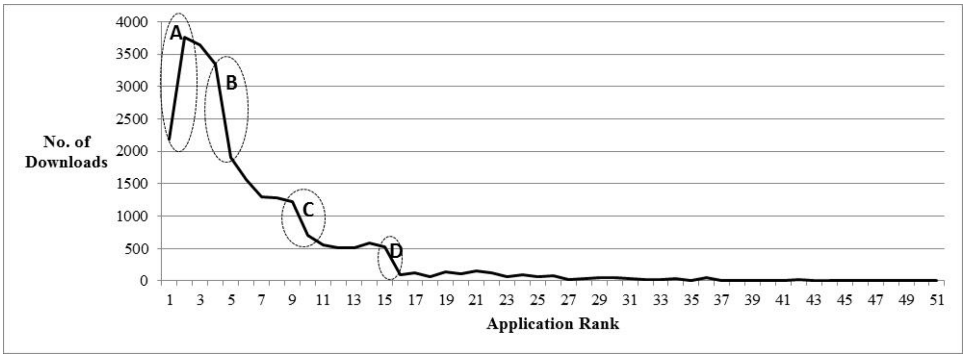
However, there are many factors affecting the extended download, and without controlling for those factors, we might reach a conclusion derived by a spurious relationship between the rank and the extended download. We identify such factors in the following section.

2.2. IT, User, and Application Characteristics and Extended Download

There are several factors which could be directly associated with the extended application download other than the application rank. Specifically, we identify several IT characteristics, user characteristics, and application type as control variables.

2.2.1. IT Characteristics

First, a mobile application downloader should pay for the mobile Internet data transmission. More specifically, s/he should pay the monetary cost for the mobile data transmission and incur the time cost for the download. Calling plans with data (500MB data cap, for example) enable us to download data with less psychological burden for the cost associated with the download. Therefore, we can expect that the data plan subscription leads to less (monetary and psychological) costs for the application download.



<Figure 1> Extended Downloads and Application Rank

Second, the network technology to which the downloader is subscribing is directly associated with the download time. For example, the average download speed of LTE network (4G-network) records 100Mbps, while 1x-EVDO network (2.5G-network) records 2.4Mbps. We consider whether the user has a data plan and the network technology to which the user is subscribing as control variables for the extended application download.

Third, device characteristics would matter for the application download. Mobile devices with better color resolution and sound, for example, can provide users with more utilities for the application usage. Consequently, better mobile interface would bring on more application downloads. We consider color, sound, and other device functions as control variables for the extended application download.

2.2.2. User Characteristics

There are several user characteristics which could be associated with the mobile application download. First, we consider hedonic-orientation of users. Consumer attitudes can largely be classified into hedonic and utilitarian, which are directly related to consumers' value assessment and decision making (Voss et al., 2003). Hedonic and utilitarian users would have different value systems on the application usage. For example, hedonic users put more values on the non-utilitarian components such as fun, exciting, and enjoyment than utilitarian components such as effectiveness, helpfulness, and practicality (Grünhagen et al., 2003; Mäenpää et al., 2006; Voss et al., 2003). Given that the intrinsic values from the variety-seeking behavior are closely related to hedonic and sensational factors (Zuckerman, 1979), we could expect users with hedonic-orientation might explore new applications more than utilitarian users, and therefore, they could have a larger propensity to the extended download. We measure the extent of hedonic-orientation of a user with the ratio of the number of hedonic application usages to the number of total application usages.

Second, the cost-benefit calculus would function less for the cost-insensitive users, and therefore, the cost-insensitivity would be related to extended application download. As such, we consider the cost-insensitivity of users. There are voice and SMS caps on calling plans in subscription and cost-sensitive users would try to minimize the over-charge for over-usages of voice or SMS. Although it would be better to change the calling plan or their calling patterns, cost-insensitive users could continue to stick to their calling patterns with the same plan. Thus, we measure the cost-insensitivity of users as their monthly average over-charge.

Third, users' purchasing power would be directly related to cost-benefit calculus, and thus, to the extended application download. We measure the purchasing power of users as their monthly average charge.

Lastly, demographic variables are known to explain large variances of outcome variables in many social science studies. We control for the age and gender of users that are known to be correlated with IT adoption (Venkatesh et al., 2003).

2.2.3. Application Type

As the stimulus from the repeated tasks in the same application decreases, our cognition works to produce more input from outside (Zuckerman, 1979), ending up finding other application to increase the level of stimulus. Typical example would be a mobile gamer who feels boredom from playing the current mobile game and is trying to seek a new game. Since the variety-seeking behavior are closely associated with hedonic and sensational factors (Zuckerman, 1979), we could expect this variety-seeking effect would be stronger in the hedonic application download and usage than in the utilitarian application. Thus, we consider application type in the analysis.

Ⅲ. Empirical Analysis

3.1. Data Description

This study uses a large dataset from a major telecommunications company in Korea. The company (and telecom companies in general) could capture its subscribers' application download and usage only over its telecom network; i.e., the application download and usage over Wi-Fi or sole-playing application usages could not be recorded in the database. To minimize the possible bias from the incompleteness of data, we collected application download behavior only from a sample of feature-phone users, who could not access the application market using Wi-Fi. Based on Contract Number (CN) and Customer Telephone Number (CTN), we randomly drew a sample of 29,936 individual subscribers and then retrieved their application download or usage data recorded for 6 months (Jan 2011-June 2011).[3] By focusing on feature-phone users, we could analyze their entire application download history during the data period without the concern of missing data.[4]

The dataset includes a variety of variables including users' application download and usage history, voice and SMS usage per month, plans (calling plan and data plan), device features, network technology for data transaction, membership period and demographic variables described in <Table 1>.

There are eight app categories in the dataset-Game, Entertainment, Phone Assortment, M-commerce, Biz-solution, Portal, Location/Traffic, Information/Life-which were classified by the telecommunications company. We regarded applications in the categories of Game, Entertainment, and Phone Assortment as hedonic applications, whereas M-commerce, Biz-solution, Portal, Location/Traffic, Information/Life as utilitarian applications.

Among the 29,936 users, we focused on users who had made an extended application download during the data period. A total of 7,877 users and their 27,824 extended downloads were kept for the main analysis.[5] <Table 2> and <Table 3> summarize the basic statistics of the main sample and variables.

To explore the role of application rank in users' extended download, we collected the application rank history as well. The rank was updated bi-weekly by the telecommunications company based on the number of downloads during the last two weeks.

3.2. Empirical Approach

To investigate the effect of rank on the extended application download, we focus on the time to the extended download (days) as the dependent variable.

3) We drew users whose CN and CTN end with 0. The last digit of CN is a random number, while CTN could be either chosen by a customer or randomly generated. If we could assume that customers are equally distributed over the last digit of CTN (i.e., 0-9), then the sample is 1:100 scale out of the population. That means the population size would be around 29,936*100=2,993,600.

4) We recognize the issue of a possible selection bias in our data by ignoring smartphone users. However, we believe their download information could be severely contaminated and unreliable, because a large portion of their application download was conducted over Wi-Fi.

5) Extended-downloaders in the dataset are significantly younger (by 4.6 years) and spent more money per month (by 11,380 won on average) than non-downloaders, but their membership periods were shorter (by 133 days).

For example, if a user downloads a new game application 30 days after s/he downloaded a game application, the time to the extended download is 30.

A user could download many applications and it is unrealistic to assume that the extended downloads by the same individual are uncorrelated with each other given the observed covariates. To capture the multi-level structure of the data, we employed a random-effects generalized least squares (GLS) regression.

In the random effect model, the total residual is estimated with two error components: ζ_j, which is shared within subject *j*, and ϵ_{ij}, which is unique for each extended download of category *i* by subject *j*. Then, the random-effect model will be,

$$y_{ij} = (\beta_1 + \zeta_j) + \beta_2 \chi_{2ij} + \cdots + \beta_k \chi_{kij} + \epsilon_{ij}$$

where y_{ij} is the time to extended download of category *i* by subject *j*, and $\chi_{2ij}, \cdots, \chi_{kij}$ are the covariates.

<Table 1> Variable Description

Variable	Description
Dependent Variable	Time to Extended Download (days)
Independent Variables	
AppRank	Application ranking in the category (A smaller value means a higher rank)
AppRank_Square	Square of application ranking
AppRank_N	Top ranking dummy (1=if the rank is equal to or less than N, 0=otherwise)
Control Variables	
IT Characteristics	
NetworkTech	Whether to subscribe to advanced network technology (0=1x_RTT or less advanced network, 1=1x_RTT or less advanced network)
DataPlan	Whether to subscribe to data plan (0=No, 1=Yes)
Sound	Sound capability (0=Less than 64 Poly, 1=Others)
Color	Color resolution (0=Less than 16 million, 1=Others)
MP3	MP3 player function (0=No, 1=Yes)
DMB	DMB function (0=No, 1=Yes)
User Characteristics	
HedonicOrientation	Hedonic-orientation (relative frequency of hedonic application usage)
MembershipPeriod	Active membership periods (days)
Age	Age (0=~10, 1=10~14, 2=15~19, 3=20~24, 4=25~29, 5=30~34, 6=35~39, 7=40~44, 8=45~49, 9=50~54, 10=55~59, 11=60~64, 12=65~69, 13=70~)
Gender	Gender (0=Male, 1=Female)
PurchasingPower	Purchasing power (monthly average charge, 1000 won)
CostInsenstivity	Cost insensitivity (monthly average over-charge, 1000 won)
Application Type	
AppType	1 = Hedonic application (Game, Entertainment, and Phone Assortment), 0 = Utilitarian application (M-commerce, Biz-solution, Portal, Location/Traffic, Information/Life)

3.3. Analysis Result

<Table 4> shows the analysis results. Time to Extended Downloads is severely positively skewed (greater than 2), thus we log-transformed the variable for the analysis. To avoid the case of 'log 0', we added a small value (0.001) to Time to Extended Download before the transformation.

The coefficient of application rank (*AppRank*) in the random-effects model (Model 1) is positive (0.003) and significant, indicating higher rank (i.e., a smaller value of rank) of a new application is positively associated with the extended download of the application. We also explore the quadratic effect of rank by including the square term of rank (Model 2), but the coefficient of the square term (*AppRank_Square*) is not significant.

The above results may imply that overall, application rank has a linear relationship with extended application download. However, previously proposed conjectures as to the effects of application rank on extended download and users' download pattern in <Figure 1> suggest that the linear relationship may be a too rough approximation of the rank effect.

Therefore, we next investigate the existence of critical point of rank effect by including dummy variables indicating the top ranked application (Model 3). Specifically, we add dummy variables, *AppRank_N*'s, whose value is 1 for an application with a rank equal to or less than N. We select the cut-off ranks (ranks 4, 9, and 16) based on the point where there is a huge drop in the number of extended downloads in <Figure 1>. The three critical points found in <Figure 1> were significant in the random effects

<Table 2> Basic Statistics of the Main Sample and Variables (Total Users=7,877)

Variable	Sample Composition / Basic Statistics
Gender (persons)	Female: 3,415, Male: 4,462
Age (persons)	~14: 1,657, 15~19: 1,982, 20~24: 800, 25~29: 747, 30~34: 612, 35~39: 571, 40~44: 515, 45~49: 385, 50~54: 265, 55~: 343
Active membership period (days)	Mean: 567.53, Standard deviation: 681.87
Data plan subscription (persons)[1]	Yes: 6,829, No: 1,048
Network technology (persons)	1x-RTT network or less advanced than 1x-RTT network: 770, 1x-EVDO network or more advanced than 1x-EVDO network: 7,107
Average call charge (Won)	41,106
Number of extended downloads	Total downloads: 27,824, Average downloads per user: 3.53
Time to extended download (days)	Mean: 6.55, Standard deviation: 11.21, Skewness: 2.87

Note: [1] Users could change their plans, but there were no users in our dataset who have newly subscribed to a data plan or cancelled their data plan during the data period. [2] Application rank is determined by the number of downloads during the last half of a month (first half or second half of a month) and updated twice a month. For example, application rank shown on May 7, 2015 is determined by the number of downloads between April 15, 2015 and April 30, 2015.

<Table 3> Number of Extended Downloads by Rank (Up to 10th Rank)

Rank	1	2	3	4	5	6	7	8	9	10
No. of Extended Downloads	2,193	3,763	3,648	3,347	1,901	1,566	1,298	1,279	1,229	698

analysis (*AppRank_4*, *AppRank_9*, and *AppRank_16*). For example, the negatively significant coefficient of *AppRank_4* (-0.48) indicates that applications ranked between 1 and 4 are more likely to be downloaded compared to the other applications. More importantly, the coefficient of the rank (*AppRank*) becomes insignificant after including the top rank dummies. Therefore, the effect of rank on extended application download exhibit a step function rather than a linear function.

The estimation results for the control variables support that the cost-benefit calculus is working in extended application download.

Among the IT characteristics, the subscription to data plan (*DataPlan*) is significant with the expected signs. Mobile users with data plan are about one and half days faster than others. However, the use of advanced network technology or device character-

<Table 4> Results from the Random-Effect Model [D.V.=ln(Time to Extended Download)]

Variable	Control Model	Model (1)	Model (2)	Model (3)
Main Variables				
AppRank		0.003 (0.001)*	0.015 (0.010)	0.018 (0.011)
AppRank_Square			0.000 (0.000)	
AppRank_4				-0.48 (0.12)***
AppRank_9				-0.37 (0.11)***
AppRank_16				-0.29 (0.13)*
Control Variables				
IT Characteristics				
NetworkTech	-0.24 (0.35)	-0.37 (0.35)	-0.38 (0.35)	-0.40 (0.35)
DataPlan	-0.41 (0.12)***	-0.41 (0.12)***	-0.41 (0.12)***	-0.44 (0.12)***
Sound	-0.16 (0.18)	-0.08 (0.18)	-0.08 (0.18)	-0.10 (0.18)
Color	0.02 (0.04)	0.01 (0.04)	0.01 (0.04)	0.01 (0.04)
MP3	-0.16 (0.22)	-0.10 (0.22)	-0.10 (0.22)	-0.08 (0.22)
DMB	0.10 (0.08)	0.11 (0.08)	0.11 (0.08)	0.10 (0.08)
User Characteristics				
HedonicOrientation	-0.91 (0.16)***	-0.94 (0.16)***	-0.94 (0.16)***	-0.92 (0.16)***
CostInsenstivity	-0.00 (0.00)***	-0.00 (0.00)***	-0.00 (0.00)***	-0.00 (0.00)***
PurchasingPower	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
MembershipPeriod	0.00 (0.00)***	0.00 (0.00)***	0.00 (0.00)***	0.00 (0.00)***
Age	-0.11 (0.01)***	-0.11 (0.01)***	-0.11 (0.01)***	-0.11 (0.01)***
Gender	0.17 (0.10)	0.15 (0.10)	0.15 (0.10)	0.15 (0.10)
Application Characteristic				
AppType	-0.37 (0.10)***	-0.38 (0.10)***	-0.40 (0.10)***	-0.35 (0.10)***
Constant	-0.85 (0.57)	-1.21 (0.61)*	-1.85 (0.79)*	-1.64 (0.57)**

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; two-tailed tests.

istics such as sound, color, and other device functions are not significant.

Regarding the user characteristics, hedonic-orientation of users (*HedonicOrientation*), cost-insensitivity (*CostInsenstivity*), active membership period (*MembershipPeriod*), and age (*Age*) are significant. Users who are more inclined to use hedonic-applications than to utilitarian applications and users with more over-charges are found to have a greater tendency toward extended application downloads. Active membership period is statistically significant, but since it has a very small coefficient, it is not economically significant (one day longer membership is associated with 0.0015 day faster download). Lastly, age is negatively associated with the time to the extended application download.

3.4. Robustness Check

A fixed-effects model can also be considered to control for time-invariant individual-specific unobserved heterogeneity. We employed a fixed effect model as well to check the robustness of the result. When the number of individuals is relatively large compared to the total number of observations, like ours, the model becomes problematic as it faces the incidental parameter problem (Baltagi, 2001). To avoid the problem, we focused on 1,847 users who did extended downloads more than or equal to six times during our data period. Note that several user-specific and technology-specific variables are excluded from the original model as the fixed-effect term perfectly control for the time invariant user heterogeneity.

Similarly to the main result, *AppRank* is positive and significant, meaning that users tend to extended-download high-ranked applications, but the main effect becomes insignificant as several cut-off points are included in the model.

Ⅳ. Discussion and Conclusion

In this study, we empirically explore how the application download rank affects users' extended mobile application download. Drawing on the rational choice

<Table 5> Results from the Fixed-effect Model [DV=ln(Time to Extended Download)]

Variable	Control Model	Model (1)	Model (2)	Model (3)
Main Variables				
AppRank		0.012 (0.005)*	0.007 (0.013)	0.011 (0.015)
AppRank_Square			0.000 (0.000)	
AppRank_4				-0.54 (0.24)*
AppRank_9				-0.19 (0.06)**
AppRank_16				-0.18 (0.10)
Control Variables				
Application Characteristic				
AppType	-0.38 (0.13)**	-0.22 (0.14)	-0.22 (0.14)	-0.15 (0.14)
Constant	-1.50 (0.12)***	-0.92 (0.25)***	-1.18 (0.72)	-1.14 (0.51)*

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; two-tailed tests.

theory and using a large transaction dataset of mobile application from a leading telecommunications company in Korea, we empirically show that higher rank of a new application could encourage extended application download, but not in a linear fashion. There are a few critical ranking points where the rank effect on the extended application download prevails but no significant rank effect is found between the critical rankings.

Our empirical result provides important managerial implications. First, the application rank promotes a diffusion of the application by accelerating the extended application download. Given that the application rank is updated based on the number of downloads during recent period (e.g., the last two weeks), the application rank and the number of extended application downloads would be in a virtuous circle, affecting each other positively.

Second, the rank effect on the extended application download is not linear but stepwise on a few critical points. Business players in the mobile application market should identify and pay attention to the critical points where they could benefit from the rank effect in the extended application download. More specifically, it would be critical to be included in a certain top-N ranks (e.g., top 9 in our dataset) for the rank effect in the extended application download, rather than competing for marginal rank increases within the range of two critical points.

From the theoretical perspective, this study has crucial implications for research on search costs and ranking effects. Our result suggests that contrary to the approach in previous studies where the effect of rank is modeled as linear or quadratic (e.g., Agarwal et al., 2011; Ghose and Yang, 2009), the effect may not follow such a smooth curve. Therefore, more fine-grained analysis of the effect would be required. Relatedly, this is the first study to examine rank effects on extended download. In ranking effect research, it would be important to distinguish initial download and extended download. Under a strong ranking effect, initial download and extended download would exhibit quite different patterns especially for high rank applications, as <Figure 1> suggests. Therefore, if both types of downloads are mixed up in a dataset, the analysis might not capture any of the distinct significant patterns.

The current study also provides implications for IT adoption literature. Given that mobile is becoming *the* main IT platform, more objective and reliable data on IT adoption and usage will be recorded and available. Therefore, IT adoption researchers should be concerned about new approaches based on the new data. When coupled with the new approach, the traditional perception-based adoption research such as TAM could provide deeper understanding of IT adoption behavior.

We conclude with limitations of this study and suggestions for future research. First, our empirical analysis focused on feature phone users who made an extended application download during the data period. Since smartphone users would find less difficulty in searching for lower-ranked applications, which are displayed, for example, in the next search result pages, the critical points of ranking effect might be less evident for smartphone users. Our study could be expandable to smartphone users by collecting data on their complete application download history through telecom networks and Wi-Fi. Second, we focused on the rank effect on the extended application download, but one may investigate the rank effect on the initial application download and compare the result with our study.

<References>

[1] Agarwal, A., Hosanagar, K., and Smith, M. D. (2011). Location, Location, Location: An Analysis of Profitability of Position in Online Advertising Markets. *Journal of Marketing Research*, *48*(6), 1057-1073.

[2] Avery, C. N., and Chevalier, J. A. (1999). Herding over the Career. *Economics Letters*, *63*(3), 327-333.

[3] Baltagi, B. H. (2001). *Econometric Analysis of Panel Data* (2nd ed.). Chichester, UK: Wiley.

[4] Banerjee, A. V. (1992). A Simple Model of Herd Behavior. *Quarterly Journal of Economics*, *107*(3), 797-817.

[5] Bang, Y., Lee, D.-J., Han, K., Hwang, M., and Ahn, J.-H. (2013). Channel Capabilities, Product Characteristics, and Impacts of Mobile Channel Introduction. *Journal of Management Information Systems, 30*(2), 101-125.

[6] Bikhchandani, S., Hirshleifer, D., and Welch, I. (1992). A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades. *Journal of Political Economy*, *100*(5), 992-1026.

[7] Dekel, E., and Piccione, M. (2000). Sequential Voting Procedures in Symmetric Binary Elections. *Journal of Political Economy*, *108*(1), 34-55.

[8] Duan, W., Gu, B., and Whinston, A. (2009). Informational Cascades and Software Adoption on the Internet: An Empirical Investigation. *MIS Quarterly, 33*(1), 23-48.

[9] Ge, X., Messinger, P.R., and Li, J. (2009). Influence of Soldout Products on Consumer Choice. *Journal of Retailing, 85*(3), 274-287.

[10] Chae, M., and Kim, J. (2003). What's So Different About the Mobile Internet? *Communications of the ACM, 46*(12), 240-247.

[11] Chung, S., and Park, C. (2007). Factors Influencing Acceptance of Mobile Services: Moderating Effects of Service Type. *Information Systems Review, 9*(1), 23-44.

[12] Ghose, A., Goldfarb, A., and Han, S. P. (2012). How Is the Mobile Internet Different: Search Costs and Local Activities. *Information Systems Research, 24*(3), 613-631.

[13] Ghose, A., and Yang, S. (2009). An Empirical Analysis of Search Engine Advertising: Sponsored Search in Electronic Markets. *Management Science, 55*(10), 1605-1622.

[14] Green, S. L. (2002). *Rational Choice Theory: An Overview*. Baylor University Faculty Development Seminar.

[15] Grinblatt, M., Titman, S., and Wermers, R. (1995). Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior. *American Economic Review, 85*(5), 1088-1105.

[16] Grünhagen, M., Grove, S. J., and Gentry, J. W. (2003). The Dynamics of Store Hour Changes and Consumption Behavior: Results of a Longitudinal Study of Consumer Attitudes Toward Saturday Shopping in Germany. *European Journal of Marketing, 37*(11/12), 1801-1817.

[17] Han, J., Kang, S., and Moon, T. (2013). An Empirical Study on Perceived Value and Continuous Intention to Use of Smart Phone, and the Moderating Effect of Personal Innovativeness. *Asia Pacific Journal of Information Systems, 23*(4), 53-84.

[18] Herrnstein, R.J. (1990). Rational Choice Theory: Necessary but Not Sufficient. *American Psychologist, 45*(3), 356-367.

[19] Jung, W., and Hong, S.-K. (2014). The Effects of Metaphors in the Interface of Smartphone Applications on Users' Intention to Use. *Asia Pacific Journal of Information Systems, 24*(3), 255-279.

[20] Li, X. (2004). Informational Cascades in It Adoption. *Communications of the ACM, 47*(4), 93-97.

[21] Mäenpää, K., Kanto, A., Kuusela, H., and Paul, P. (2006). More Hedonic versus Less Hedonic Consumption Behaviour in Advanced Internet Bank Services. *Journal of Financial Services Marketing, 11*(1), 4-16.

[22] McGarty, C., Turner, J.C., Oakes, P.J., and Haslam,

S.A. (1993). The Creation of Uncertainty in the Influence Process: The Roles of Stimulus Information and Disagreement with Similar Others. *European Journal of Social Psychology, 23*(1), 17-38.

[23] Nelson, P. (1974). Advertising as Information. *Journal of Political Economy, 82*(4), 729-754.

[24] Oh, S. (2014). A Study on the Determinants of Mobile Application Purchase based on User Groups. *Information Systems Review, 16*(1) 73-88.

[25] Oh, W., and Jeon, S. (2007). Membership Herding and Network Stability in the Open Source Community: The Ising Perspective. *Management Science, 53*(7), 1086-1101.

[26] Shiller, R. J. (1995). Conversation, Information, and Herd Behavior. *American Economic Review, 85*(2), 181-185.

[27] Vatanparast, R. (2009). Theories Behind Mobile Marketing Research, In K. Pousttchi and D. G. Wiedemann (Eds.). *Handbook of Research on Mobile Marketing Management,* 255-278, IGI Global 2009.

[28] Venkatesh, V., Morris, M.G., Davis, G.B., and Davis, F.D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly, 27*(3), 425-478.

[29] Voss, K.E., Spangenberg, E.R., and Grohmann, B. (2003). Measuring the Hedonic and Utilitarian Dimensions of Consumer Attitude. *Journal of Marketing Research, 40*(3), 310-320.

[30] Zhang, D. (2007). Web Content Adaptation for Mobile Handheld Devices. *Communications of the ACM, 50*(2), 75-79.

[31] Zuckerman, M. (1979). *Sensation Seeking: Beyond the Optimal Level of Arousal.* Hillsdale, NJ: Erlbaum.

◆ About the Authors ◆

Youngsok Bang

Youngsok Bang is an Assistant Professor in the Department of Decision Sciences and Managerial Economics at the Chinese University of Hong Kong (CUHK). He received his B.S., M.S., and Ph.D. degrees in Management Engineering from Korea Advanced Institute of Science and Technology (KAIST) and his second Ph.D. degree in Information Systems from McGill University. His current interests lie in the business value of big data, especially in the areas of mobile commerce and social media. His research has appeared in *MIS Quarterly, Journal of MIS,* and several other journals.

Dong-Joo Lee

Dong-Joo Lee is an Associate Professor at the Division of Management, Hansung University, in Seoul, Korea. He holds a Ph.D. in Management Engineering from the Graduate School of Management, KAIST. His research interests include electronic and mobile commerce, information privacy, and information systems economics. His work has appeared in several journals, including *MIS Quarterly, Journal of MIS, Long Range Planning, International Journal of Information Management, European Journal of Operational Research, Technovation, and Knowledge Management Research and Practice.*

Submitted: December 31, 2014; 1st Revision: May 21, 2015; Accepted: July 10, 2015