Hindawi
Mobile Information Systems
Volume 2017, Article ID 3894685, 13 pages
https://doi.org/10.1155/2017/3894685

Research Article

The Effects of Consumer Innovativeness on Mobile App Download: Focusing on Comparison of Innovators and Noninnovators

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Received 14 July 2017; Revised 9 October 2017; Accepted 2 November 2017; Published 19 December 2017

Academic Editor: Xiapu Luo

In the new market for mobile apps, innovators, that is, early adopters of new products, have drawn attention from various researchers for their role in contributing to the success of a product. Due to the discrepancies between findings in these studies, a research framework and empirical model must be established to demonstrate how innovators affect the market for mobile apps in comparison to other types of users. To clarify the empirical basis on which innovators contribute to market development, we compare mobile app download patterns between innovators and noninnovators. Using the app download data of actual users in one of the largest app markets in Korea, we compare and analyze download behavior for a period of less than two years following their subscription to the market. The empirical analysis reveals that the download volume of innovators remains constant over a long period, while for noninnovators, volume is initially high, reflecting their interest in downloading, but it rapidly decreases thereafter. The results of this study have practical implications for companies seeking to assess the market value of innovators.

1. Introduction

How can we predict the process of developing the mobile app market? Do really innovators play an important role in the app market for the long term, such as in other new technology markets? Recent advances in mobile information technology have resulted in exponential diffusion of mobile devices among consumers of all ages. This feverish activity in the mobile environment has in turn triggered the rapid growth of the software market, including content for use on those devices. In the rapidly growing mobile content market, various mobile applications have become popular, including those that allow users to search for information on the Internet, watch videos, and play games. The IDC (2013) forecasted that the volume of the annual mobile application market would increase from $88 billion in 2013 to $187 billion in 2017 and that the sales revenue from mobile devices would increase from $10 billion in 2013 to $25 billion in 2017 [1]. This remarkable growth in the mobile application market will undoubtedly provide new opportunities for many companies; in light of this trend, consumers' application usage behaviors have a crucial meaning for these firms.

In this time of opportunity, practitioners launching new products such as mobile devices and applications for them must consider innovators, or early adopters of new products, and the relationship between the diffusion of new products and innovativeness, or users' willingness to be among the first to use them. In fact, research has found that understanding and prediction of innovators' behaviors is the key factor in the success of new, technology-intensive products [2, 3]. Innovators perceive themselves to be more active disseminators of new products than others [4–6]. Calculating the number of innovators has the advantage of enhancing the ability to predict the final market size [7]. Consequently, a scale to measure consumers' innovativeness has been developed [8] and analyzed using marketing models [6, 7, 9]. Several previous studies have expounded the significance of studying innovators' behaviors and applying the results to new product markets such as the mobile market.

The roles of innovators in the success of new products such as mobile apps may be summarized as follows. First, innovators are faster adopters of new products compared to followers [7], and, accordingly, they can facilitate

companies' efforts to spread these products. To increase the initial market share of a new product, companies must mobilize a sizable consumer group, targeting those consumers who are inclined to adopt it in its early days. Innovators are motivated to adopt new products ahead of others in their social networks because acquiring knowledge of new products not yet experienced by others enhances their social status and puts them in the opinion leader position [6]. Second, innovators tend to purchase and explore new products voluntarily and actively recommend them to others. The motives of word-of-mouth activity may be related to the social activities and status of innovators. Researchers have also posited that innovators with greater knowledge tend to be heavy users of products who can affect others' purchasing of those products [10]. Third, early adoption and heavy usage often overlap [8]. Innovators frequently have a high level of product knowledge and expertise due to greater consumption. The more frequently a person uses new products, the more status and opinion leadership he or she will enjoy [6].

While the results of previous studies provide some guidelines for marketing managers, the roles of innovators versus noninnovators in the performance of new products have not been sufficiently clarified. Previous studies tend to expound the advantages of innovators because they purchase new products much more frequently than noninnovators [8, 11, 12]. In general, heavy users evaluate new products promptly and adopt them quickly [10]. Nonetheless, it may be that not all innovators are heavy users. In fact, one study reported that differences in usage volume between innovators and noninnovators were not significant [7]. In addition, many previous studies mainly engaged in (1) comparing the level of innovativeness between heavy users and general users [12], (2) examining the relationship between general consumer innovativeness and usage in a specific category [11], and (3) examining usage behaviors in the context of adopting new equipment [10]. Unfortunately, few researchers have compared product usage between innovators and noninnovators of new virtual goods directly.

The second limitation of previous studies is that they relied too much on cross-sectional methodology despite the value of using long-term data. In research on innovation and mobile content, actual usage data must be analyzed in the long term in order to provide valid results that are not possible to obtain using cross-sectional survey data. Previous studies posit that innovation of mobile services provides usefulness and ease of use to the consumer, thereby promoting adoption of new products. However, these studies focus on consumers' response to questionnaires rather than using actual mobile usage data [13]. Other limitations are related to measuring innovativeness. In previous studies, innate innovativeness was measured by referring to the level of abstraction [3]. This approach to measurement assumes that consumer innovativeness can be represented by numerous general characteristics in studies of wide scope. Accordingly, it is limited in its ability to predict consumer behaviors in specific categories. Furthermore, cross-sectional survey data are inappropriate for analysis of the long-term relationship between innovativeness and heavy usage. Therefore, additional research is required in order to elucidate the exact dynamics of cross-temporal variations in innovative consumer behavior by measuring behavioral innovativeness in specific categories [6].

Based on the findings of various marketing, sociology, and information system studies, we present this study with the following research objectives. First, we compare consumption of mobile content between innovators and noninnovators in the expanding market for mobile apps. Then, based on the results of the first comparison, we conduct a second comparative analysis of the degree to which these two groups contribute to the success of the market for mobile apps and the importance of their contributions. Third, using an empirical model and long-term data, we measure consumer behaviors in the mobile market, comparing the behaviors of innovators and noninnovators.

We thereby contribute to the mobile marketing literature in various ways, which may be summarized as follows. First, the findings of this study enhance our understanding of the behavioral differences between innovators and noninnovators over a long period of time. As mentioned above, previous studies on consumer variations in innovativeness [10, 13] used cross-sectional data and focused on the psychological mechanisms underlying innovative behavior. In addition, we observe the actual behavior of consumers in the long term and interpret changes in behavior in the two groups in terms of actual market performance. Comparing the behavior of mobile app consumers against the backdrop of differentiation in the lower category of apps, we expand the findings of previous studies on innovativeness in a single category [6, 8]. Lastly, in measuring innovativeness, we utilize actual data accumulated from the date of launching of the mobile devices included in this study. This approach enables us to observe the behavior of consumers who are introduced for the first time to new products directly. These data are more appropriate for an accurate measurement of the behavior of innovators in the rapidly growing mobile market. Our systematic approach to collecting and analyzing these data for the study of innovators' consumption behavior is unique in research in this area.

In this study, we analyze the behavior of mobile application users in one of the largest app markets in Korea, by the pseudonym Goapps.com. The data collected include both records of consumer downloads on mobile devices following their subscriptions after the opening of the market and various variables related to consumer usage of mobile devices. The period of analysis was 1 year and 11 months, starting from the date of the first app download by each consumer new to the app market. These data are well suited to identification of the behavior of innovators, as they provide consumer records on downloads of various apps over a long period of time. We can therefore observe the time of selection and the type of apps downloaded at the consumer level and analyze how consumer characteristics affect the demand for apps. The data are also useful for measuring innovativeness because they are actual data rather than data self-reported from a questionnaire. To measure innovativeness on the basis of download behavior, we classify innovators and noninnovators at a particular point

in time [7], observing download patterns from the date of market launch. The results provide statistical proof of what point in time is optimal to discern innovativeness specific to mobile apps. Finally, the app market data used in the analysis in this study represent the mobile app industry well, thereby increasing the possibility of generalizing the results. The Korean app market is regarded as highly significant in the global app market [14]. In this market, innovativeness and acceptance of information technology account for a large part of consumers' product selection. Accordingly, this market has been often studied for innovativeness in information and communication products [7, 9].

2. Preliminary Analysis and Conceptual Framework

2.1. Innovators in App Markets. Innovativeness is related to consumer-purchasing patterns at the early stage in a product life cycle [4], consumers' tendency to be interested in a variety of products [8], and voluntary searches for product information [6]. In previous studies, the most-often cited characteristic of innovativeness in early adopters of a product is the ability to be relatively quick in purchase decision-making. Innovators are eager to demonstrate their early acceptance of new products and technologies to other social groups. In this regard, innovators may be defined as first adopters of certain products and technologies in their social networks [7]. Also, in previous studies, innovators are defined as a minority group (less than 2% of all product adopters). Consumers in this group tend to find satisfaction in the fact that they are the first to experience and evaluate new technology in their social networks. This technological pioneering boosts their self-recognition and puts them in a superior social position relative to other groups in terms of knowledge and experience. Innovators prefer the freshness of a new product in itself and are willing to pay a higher price for it in order to be first. On the other hand, consumers in the noninnovator group place more emphasis on the practical utility deriving from the functions and economic value of the product. Accordingly, unlike innovators, noninnovators are more reluctant to pay a high price for newness [8].

Before comparing the behaviors of innovators and noninnovators, we herein define the metrics by which we distinguish the former from other types of consumers. In previous studies, innovators and noninnovators have been measured and classified according to various criteria. Purchase decision time (e.g., adoption time) is the most representative reference variable. In the study of Goldenberg et al. [7], the innovator group was defined by the standard of receiving content online, whereby innovators were significantly faster than noninnovators in terms of adoption time. In line with these earlier studies, we also utilize app adoption time for the mobile consumer as the criterion distinguishing innovators from other groups. That is, consumers who enter the mobile market at an earlier date are classified as innovators; those who enter it at a relatively later date are classified as noninnovators. For the purposes of statistical analysis, we also verify the exact adoption time through analysis of actual data.

To measure innovativeness in the app market, previous studies focused either on attitude [8, 10, 13] or on behavior [4, 6, 7]. This study focuses on behavior as the criterion measuring innovativeness, specifically, behavior-based innovativeness. For this purpose, we investigate consumer entry into the app market. The data reveal that nearly all consumers in this study had used old mobile devices but switched at some point to smart phones, enabling app usage. (Most apps can be downloaded and used only on smart phones.) Accordingly, these consumers entered the app market after their adoption of a new technology, the smart phone. Likewise, we posit that consumers in the app market will first adopt these devices prior to the adoption of the apps. Therefore, we also explore the differences in adoption patterns of both units (hardware) and apps (software).

In this study, consumers using Goapps.com are separated into innovators and followers. A preliminary analysis is performed to compare the characteristics of the two groups. The analytical data include records of consumers' behaviors on Goapps.com from January 2009 to January 2011. The consumer sample consists of 336 people randomly chosen from the pool of all subscribers. In total, they downloaded apps 5,395 times. For enhanced reliability of the analysis results, consumers with fewer than 5 downloads during the analysis period are excluded from the analysis. In consequence, the data for analysis are reduced to 258 consumers and 5,170 downloads in total. The time unit of analysis is the month, and three types of data are analyzed: (1) app download records, (2) mobile device usage records, and (3) demographic information. The app download records include relevant variables such as the type of app and download time. The mobile device usage records include relevant variables such as consumers' voice traffic fees, text and Internet traffic fees, and device prices. The demographic characteristics include age, gender, income, and residence. In general, since consumption behavior may be affected by both environmental factors and external characteristics, we examine the roles of various elements relevant to app downloading.

Figure 1 shows trends in the cumulative number of smart phone users and app users. Together, these numbers illustrate the patterns of diffusion of smart phone devices and the inflow of smart phone users into the app market. During the first one-year period, consumer inflow into the app market increased only sluggishly; however, a rapid increase occurred in October and November 2009 (i.e., the first tipping point). Subsequently, exponential growth is evident in May and June 2010 (i.e., the second tipping point). These two periods represent the cumulative inflow of followers. Hence, from Figure 1, we are able to identify the empirical criteria with which to divide app consumers into the innovator group and the follower group. Tipping points have been used as the criteria with which to distinguish between innovators and followers in previous research [4]. This approach is therefore adopted in this study. We take the average of the tipping points in the app market and utilize this as a way to classify innovators at the point in time by which 20% of consumers in the sample have entered into the app market from its inception date. Accordingly, those consumers who adopted

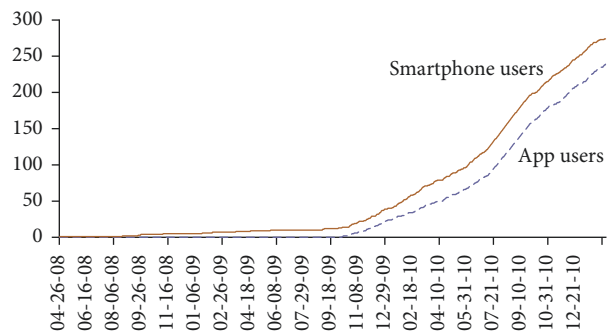

Figure 1: Patterns of consumer entry into Goapps.com.

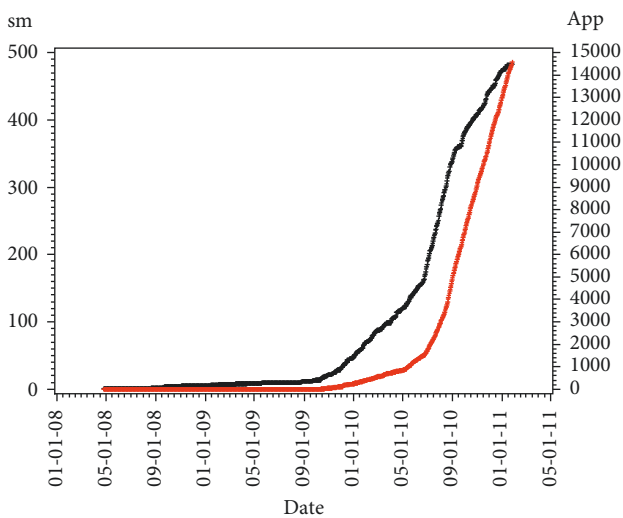

Figure 2: The number of the apps available to Goapps.com users and the total number of downloaded apps.

apps prior to May 2010 are classified as innovators and those who adopted them later as noninnovators.

Since several consumers may download one app over time, the total number of app downloads is always equal to or greater than the number of varieties of apps. The number of kinds of apps increases explosively over time in the data (Figure 2). This expansion of the market means that consumers enjoy more and more alternatives in the market, which tends to induce more consumption on average and provide greater utility to consumers, given the same conditions [15], because the larger number of alternatives increases the opportunity for consumers to choose the products they want most. In addition, increasing the number of alternative brands available to satisfy customers tends to increase the number of customers acquiring products from enhanced categories or induce the same customer to select more than one product within a certain time period (i.e., heavier usage) [10]. Accordingly, we deduce that a greater number of apps available in the market will increase the probability that consumers will download them. Based on this discussion, we posit that a change in the market (i.e., environmental factors such as the variety of apps) may have long-term positive effects on app usage. This fact needs to be taken into account during our analysis of long-term data. Therefore, these market environmental factors are included in the analytical model outlined in the following sections.

2.2. Innovators and Noninnovators. The following question naturally arises: what intrinsic differences can be identified between the two groups, innovators and noninnovators, based on the information about app adoption time? In answering this question, we expect to demonstrate the validity of measuring innovativeness using adoption time as the determining factor. To find the answer, we examine the differences between the two groups in terms of demographics and mobile device usage behavior. Demographic characteristics are external features such as age, gender, and income. Usage patterns are the behavioral characteristics associated with app usage, such as voice traffic fees and text and mobile Internet traffic fees. Previous studies have suggested that innovators, on average, are more likely to be young and male [7]. It is also more likely that consumers in this demographic are heavy users in terms of product purchase volume and usage frequency [8]. In this study, we test these assertions by comparing the demographic characteristics and mobile device usage frequency between the two groups.

Table 1 shows this comparison. For the demographic characteristics, no significant differences in age, gender, income, or residence are evident between innovators and noninnovators. However, some nonsignificant trends are discernible. There may be a tendency for innovators to be young (innovators = 30.214, noninnovators = 32.389), male (0.464, 0.554), and have higher income (0.428, 0.359). These findings are consistent with the characteristics distinguishing innovators from noninnovators in other categories such as PC usage [16] and online content [7]. However, the lack of significance may have been due to the smaller size of the sample of innovators compared to that of noninnovators. In any case, these results indicate that the groups of innovators and noninnovators are heterogeneous by the adoption time criterion.

As for the characteristics of mobile device usage, the device purchase prices and voice traffic fees are not significantly different between innovators and noninnovators. While there seem to be significant differences in the fees for text traffic and data traffic, these differences are actually not significant due to the excessively wide dispersion of the variables. This result indicates heterogeneity within the whole innovator group and within the noninnovator group. Subject to these limitations, the results may be interpreted to signify the following points. First, innovators do not pay more (i.e., higher product purchase prices) than noninnovators. This result may cast doubt on the effectiveness of the skimming pricing strategy many managers used to target innovators in the app industry. In the skimming strategy, the initial price is set at a higher level based on the expectation that market innovators will be willing to pay a higher price in order to enjoy the benefits of being opinion leaders. This strategy has been widely adopted in marketing of innovative products such as apps and smart phones. This study has revealed, however, that the marginal effect of the difference

Table 1: Demographics and mobile device usage in the two groups.

	Innovators		Noninnovators		t-value
	Mean	SD	Mean	SD	
Demographic characteristics					
Age	30.214	12.256	32.584	11.823	1.29
Gender (female = 1)	0.464	0.503	0.553	0.498	1.19
Income (more than $100,000 per year = 1)	0.428	0.499	0.346	0.477	1.10
Residence (urban area = 1)	0.463	0.503	0.445	0.498	0.25
Features of mobile device usage					
Purchase price of mobile device ($)	126.786	88.134	121.165	100.014	0.50
Voice traffic fees per month ($)	30.874	19.823	32.782	17.737	0.65
Number of text messages per month	534.855	965.136	435.423	612.502	0.97
Mobile Internet traffic fees per month ($)	4.192	10.833	5.660	10.868	0.90
Observations	56		202		

in price is greater in innovators than in noninnovators. Hence, application of the skimming strategy should be carefully reviewed prior to undertaking. Second, innovators in the market for mobile apps are more easily inclined to utilize the latest means of communication (i.e., SMS, mobile Internet usage) rather than traditional voice communication. Since mobile apps combine both text and images, this may be one reason that innovators are more actively engaged in app usage and downloads than noninnovators. Accordingly, we now launch a comparison of patterns in app usage between the two groups in order to validate the findings of previous studies that innovators are heavy users.

For comprehensive understanding of the behaviors of innovators in the app market and to enhance the efficiency of marketing activities, we herein attempt to distinguish the behaviors of innovators and noninnovators. First, innovators can be "seeding targets," playing an important role in the initial distribution of a product. The significance of the initial distribution in new markets has been emphasized in numerous previous studies [2–4]. Innovators actively engage in word of mouth, providing valuable feedback and contributing directly to product diffusion. In the context of the app market, the more interest the innovators have in new apps, the greater awareness the followers will have of those products. Using the feedback of innovators, companies may improve the quality and functionality of their apps. Innovators have strategic potential to lay the groundwork for followers to enter the market; they play a decisive role in promoting new app products and pushing potential users to the tipping point.

Innovators also enter markets while they are still immature. In this regard, they help companies build their cost and revenue structures. In concrete terms, companies must make large investments as a necessary condition for market growth. As shown earlier, however, fewer apps of lesser variety are available in the initial stages of market development; rapid growth is evident at later stages. Thus, at the time of innovators' adoption of the technology, the market lacked sufficient product variety. It seems plausible, therefore, that the merit and utility of the app market was initially low. In this situation, innovators entered the market because they were motivated by the newness of the market itself [6]. In this initial market, during which app developers were keeping initial expenses low, innovators chose to adopt their products, thus providing direct assistance to these companies in terms of cost and revenue.

In addition, innovators have the potential to be heavy users of new products. As shown in the exploratory analysis, early adopters of mobile apps (innovators) have been identified as heavy users of text and imaging services provided by mobile carriers. We therefore infer that extensive use of mobile devices for Internet access, text messaging, and voice communication will enhance users' accessibility, familiarity, and knowledge of other software. Accordingly, when innovators encounter apps with multimedia capabilities, they are likely to become heavy users in the app market. One of the crucial objectives for enterprise marketing researchers is to explore the potential of innovators and make efforts to promote them to the status of heavy users who can directly benefit the companies' revenues.

2.3. App Downloads of Innovators. We now compare in detail the differences in app usage patterns between innovators and noninnovators. Certain descriptive differences in the characteristics of mobile device usage between the two groups have already been presented. We have shown that innovators spend more time with mobile devices, particularly engaging with apps that involve multimedia. These heavy users differ in many ways from noninnovators. Innovators may or may not use more apps than noninnovators. We now present a hypothesis regarding innovators' behaviors, conducting an exploratory analysis and presenting a detailed model.

2.3.1. Longitudinal Behavior of App Users. To determine if innovators in the mobile app market use more apps, we investigate users' behavior from the longitudinal perspective. Iyengar et al. [6] empirically analyzed the tendency of innovators to engage in more product consumption than followers over the long term. Innovators not only begin to use products earlier than others, but they also use them more frequently in the long term. In line with these previous

findings, we explain the reasons for this greater usage as follows.

First, innovators embrace adoption of new products ahead of others and thus have longer periods of usage, during which they accumulate considerable knowledge about the products. In terms of cumulative purchase volume, therefore, innovators always purchase more than noninnovators overall, assuming that both groups purchase the products in almost the same volume on a periodic basis. Furthermore, innovators experience products for longer, thereby acquiring a higher level of understanding and evaluative ability [7]. This increases their chances of making additional purchases more frequently in the future. Their higher level of understanding often results in purchase-expanding behavior, in which they are likely to purchase other similar products. In a market replete with similar products (e.g., the app market), consumers are motivated to buy popular products according to their inclination in terms of risk recognition and avoidance [8]. In addition, consumers with cumulative experience have greater ability to evaluate products and more opportunities to evaluate and choose unpopular products. They gain competence to overcome the barriers involved in purchasing risky products by evaluating the products themselves based on accumulated knowledge.

Innovators must use many products to retain their expert status in their social networks. As experts, they play a central role in evaluating new products. To maintain this social position, they must demonstrate that they are actively acquiring and using new products, which is an effective means of appealing to others. Extensive usage allows them to learn about new products in the same category easily [6, 8]. They seek information on new products, thereby staying abreast of market trends. Through their personal experience with products, they aid in new product diffusion. Their ability to provide high-quality information to their neighbors in their social networks ensures their social status [7]. Accordingly, those consumers who demonstrate their innovativeness in order to retain their status in their social networks tend to be heavy users. Apps for mobile devices belong to the product category requiring personal experience for accurate product evaluation (i.e., they are experience goods). For dissemination of these products, word of mouth from opinion leaders is a crucial factor determining product performance in the market.

Innovators purchase and use products for a longer time; they tend to purchase products in larger volume more frequently in comparison with noninnovators. Iyengar et al. [6] conducted research on innovators in the medical field. They found that medical doctors differed in terms of the speed with which they adopted a new drug at the time of product launch. A particularly noticeable finding is that those who adopt new drugs ahead of other physicians tend to prescribe these new drugs more often and in larger doses than others. That is, innovators display the tendency to adopt new products more speedily and to use them more heavily than noninnovators. In addition, they demonstrate opinion leadership behaviors, introducing new products to noninnovators and taking the initiative in spreading their opinions in the market in order to demonstrate the benefits of the products they have adopted. Therefore, they bring important direct and indirect benefits to companies.

To summarize, innovators in the app market are those who enter the app market earlier than noninnovators and indulge in the usage of apps for a longer time. They use a greater variety of apps by utilizing the knowledge accumulated during the usage period. In addition, innovators endeavor to maintain their social status by displaying to others their knowledge of the products. It is advantageous for them to accumulate usage experience and advanced knowledge of various products. Accordingly, we predict that innovators will have a higher degree of usage on average than noninnovators over the long term.

2.3.2. Exploratory Analysis. In order to examine the download behaviors of innovators and noninnovators, we focus on the average number of monthly downloads by users from the first market entry by members of the two groups to the final data observations in November 2011. We predict that innovators will have higher download counts on average than noninnovators during the study period. As shown in Figure 3, however, this prediction is hard to verify. In Figure 3(a), the horizontal axis corresponds to the calendar month, displaying in a time series the number of downloads by innovators and noninnovators. This figure reveals that both groups reach the highest number of downloads 3 to 4 months following initial product adoption. This may signify that these users need a long time to accumulate experience and knowledge of apps in order to be ready to engage in real usage. Figure 3(a) confirms that innovators do not download more apps than noninnovators on average.

By contrast, in Figure 3(b), the horizontal axis represents consumers' adoption time corresponding to the number of months (starting from number 1 for the month of initial product adoption). Here, the download patterns are somewhat different between innovators and noninnovators. In the case of innovators, the download pattern shows no discernible sign of decrease, whereas in the case of noninnovators, it shows a rapid decrease. From this observation, we may infer that noninnovators rapidly depart from the app market after a certain point in time. In Figure 3(b), however, no discernible sign is evident of more downloading by innovators in comparison with noninnovators. In October 2014, innovators' download counts begin to surpass those of noninnovators (i.e., lines for the two groups intersect).

To explain why innovators have lower download counts than noninnovators and why the two download patterns intersect, we may infer as follows. Over time, the number of available app alternatives increases along with the growth of the app market. Innovators entered the market in the early stages, whereas noninnovators did so after the market had already been established. Therefore, at the time of their entry into the market, the two groups were exposed to quite different situations in terms of the available kinds of apps in the market. In fact, the app market began to grow explosively in the period from September to December 2010 (Figure 2). For those users who subscribed to the market after this

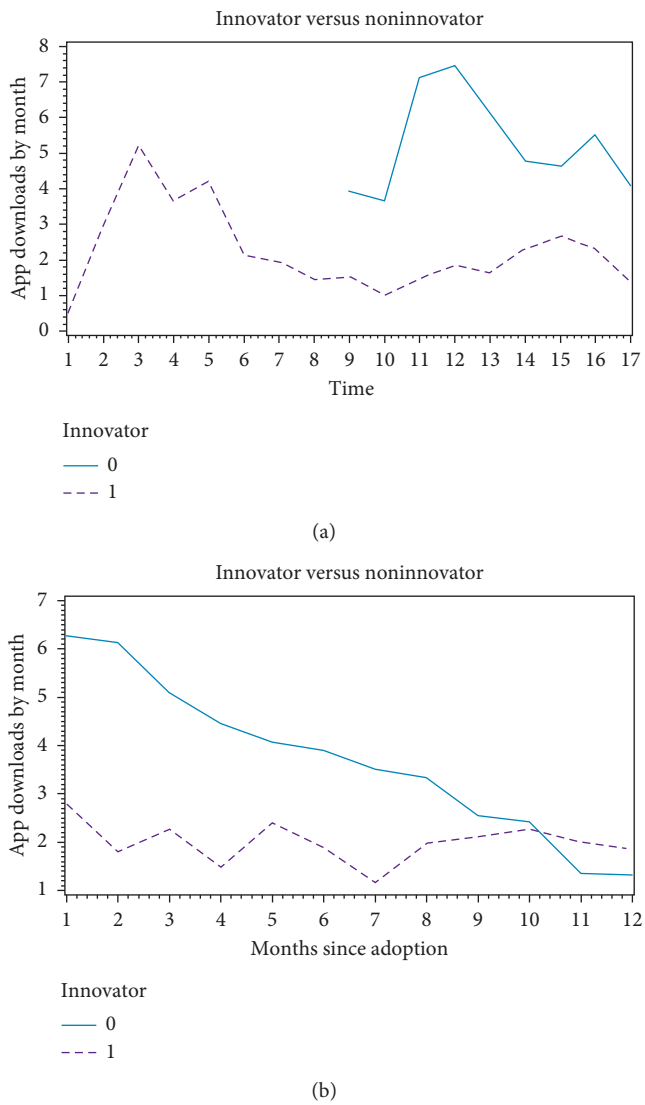

Figure 3: App downloads of innovators versus noninnovators by month. (a) Calendar-date standard and (b) adoption-point-in-time standard.

tipping point, the number of attractive apps available to customers was considerable, providing ample opportunities for downloads. Another notable point is that the probability of downloading may have been actively facilitated by aggressive push marketing campaigns. For example, advertising and promotion of apps through mass media on a large scale and buzz marketing may have had an effect. Thus, consumer awareness may have increased, with the effect of inducing the downloading of more apps.

Despite the logic that innovators may download more apps than noninnovators, this exploratory investigation produced no evidence that innovators in the app market are heavy users. This result may have occurred due to the fact that noninnovators entered the market at the time of explosive growth. Accordingly, more in-depth and systematic investigation is necessary. Therefore, we now estimate and compare actual app download patterns of innovators and noninnovators using a regression test model.

3. Model and Measurements

This section presents a model of the differences in patterns and frequency of app usage between innovators and noninnovators. For a systematically accurate analysis, the model must satisfy the following conditions: first, it should allow us to analyze long-term usage patterns of various app consumers. Accordingly, the model should be panel-based for optimum data measurement and analysis. Second, it should have proper features with which to identify and compare the differences between innovators and noninnovators. For this purpose, it must be built in a specifically parsimonious manner, competently displaying the differences between the two groups. For example, Iyengar et al. [6] used dummy variables on the consumer level to measure the behaviors of innovators.

$AppDN_{it}$ is a dependent variable in this model corresponding to the app usage of mobile device users. It is measured by counting the number of app downloads by consumer i at time t. The sample includes only those consumers who have some experience downloading more than one app (i.e., an app adopter). Observations are monthly. The dependent variable, $AppDN_{it}$, is a continuous integer with a value of more than 0. Hence, to be consistent with the dependent variable, a linear regression model wherein the error terms of ε_{it} follow the normal distribution is suitable for this study.

$$\begin{aligned} AppDN_{it} = & \beta_0 + \beta_1 \cdot NonInnovator_i + \beta_2 \cdot MonthsAdop_{it} \\ & + \beta_3 \cdot NonInnovator_i \cdot MonthsAdop_{it} \\ & + \beta_4 \cdot MonthCalendar_{it} + \beta_5 \cdot Age_i \\ & + \beta_6 \cdot Gender_i + \beta_7 \cdot Income_i + \beta_8 \cdot Voice_i \\ & + \beta_9 \cdot Sms_i + \beta_{10} \cdot Data_i + \beta_{11} \cdot Price_i + \varepsilon_{it}. \end{aligned} \tag{1}$$

$AppDN_{it}$: the number of app downloads by consumer i at time t, $NonInnovator_i$: whether or not consumer i is a noninnovator (1 = noninnovator, 0 = innovator), $MonthsAdop_{it}$: months since entry into the app market by consumer i at time t, $MonthCalendar_{it}$: calendar month of downloads by consumer i at time t, Age_i: consumer i's physical age, $Gender_i$: consumer i's gender, $Income_i$: household income of consumer i, $Voice_i$: consumer i's voice traffic fees per month on average for the last 6 months, Sms_i: consumer i's number of text messages per month on average for the last 6 months, $Data_i$: consumer i's data traffic fees per month on average for the last 6 months, $Price_i$: price paid for consumer i's mobile device.

The number of app downloads is effectively determined by the innovativeness and experience of the consumer and market conditions. Accordingly, innovativeness, $NonInnovator_i$, which is the most crucial explanatory variable, refers to whether or not consumer i is an innovator. The criterion of innovators is time-based; consumers who subscribed to the market site prior to May 2010 are classified as innovators, whereas those who did so after May 2010 are classified as noninnovators. Next, the variable

Table 2: Summary statistics for variables included in the model.

Variables	Observation	Mean	SD
Dependent variables			
Number of app downloads in one month	2,492	3.638	6.862
Innovativeness			
Noninnovator dummy	258	0.783	0.413
Time control (user level)			
Months since adoption	2,492	5.759	3.504
Time control (market level)			
Calendar month of initial download	2,492	12.241	3.504
Demographic control variables			
Age	258	32.070	11.934
Gender (female = 1)	258	0.535	0.500
Income (more than $100,000 per year = 1)	258	0.364	0.482
Region (urban area = 1)	258	0.450	0.498
Device usage control variables			
Purchase price of mobile device ($)	258	12.139	9.751
Voice traffic fees per month ($)	258	32.368	18.187
Number of text messages per month	258	456.997	631.306
Mobile Internet traffic fees per month ($)	258	5.342	10.856

$MonthsAdop_{it}$ is measured by counting the number of months at time t from consumer i's entry into the app market. The application of these variables enables us to observe changes in app download patterns over time, which is a major objective of this study. β_0 indicates the baseline download by innovators, while $\beta_0 + \beta_1$ represents that of noninnovators. If innovators download more apps than noninnovators, as predicted herein, β_1 will tend to be negative. Furthermore, if the analysis reveals a decreasing trend in app downloads by consumers over time, β_2 will be negative.

The app market environment encompasses the number of available apps in the market and consumer awareness in the market. When the number of available apps is increasing and consumer awareness is being heightened by active company marketing, the probability of more apps being downloaded will progressively increase. While this premise is plausible, we utilize calendar dates as a proxy for measurement of the app market environment in this study [6]. Specifically, the variable $MonthCalendar_{it}$ is measured by the calendar month, time t, during which consumer i downloaded the app. As noted above, with the passage of time, the app market monotonically increases and corporate marketing activities began accordingly. This measurement method presupposes that the market's environmental factors also increased linearly. As the market matures, the probability of more apps being downloaded will correspondingly increase. Hence, it is predicted that β_4 will be positive.

A variety of demographics and behavioral control variables are included in this study to represent accurately the app download patterns reflecting the changes in experience of and differences between innovators and noninnovators over time. Thus, we consider external demographic variables such as Age_i and $Gender_i$ as well as other variables related to social class and consumption patterns, such as an income dummy variable, $Income_i$. To measure income, we consider any consumer earning more than USD $10,000 to be high-income earners (i.e., $Income_i = 1$). To characterize mobile device usage, we incorporate the variable $Price_i$ to represent the price of the mobile device purchased by consumer i. A higher-priced device may indicate that the consumer is more likely to use the mobile device frequently. Other variables considered in the study include the average monthly voice traffic fees, $Voice_i$, monthly text message traffic fees, Sms_i, and monthly mobile Internet traffic fees, $Data_i$. These variables are intended to control for changes in app download patterns caused by familiarity with the mobile device itself and usage experience.

Table 2 provides the summary statistics for all variables in the model. The independent variables (months since adoption, calendar month of first download) and the dependent variable (number of app downloads) are both measured at the level of consumer i and time t. On the other hand, the dummy variable measuring innovativeness is measured at the level of consumer i based on the assumption that it remains constant at the consumer level during the observation period. In addition, the demographic and device usage variables are also measured at the level of consumer i. These variables and their measurement have the advantage of versatility; they can be utilized in various online and mobile markets. For example, while Goapps.com is not yet exercising target-marketing strategies at the consumer level, it may enforce strategies differentiating consumers and download times using the variables included in this study.

4. Empirical Findings

In this study, we compare the app download patterns between innovators and noninnovators, presenting an

Table 3: Main results of the regression model 1: base model.

Variables	Base models	
	Model 1-1: no market control	Model 1-2: market control using calendar month
Intercept	2.146** (0.515)*	−0.139** (0.576)*
Noninnovator	4.578** (0.631)*	−0.230** (0.084)*
Months since adoption	0.008** (0.059)*	−0.336** (0.088)*
Noninnovator × months since adoption	−0.464** (0.088)*	−0.715** (0.103)*
Calendar month	—	0.761** (0.090)*
Demographic control variables		
Age	0.134 (0.137)	0.075 (0.135)
Gender (female, %)	−1.053** (0.271)	−1.261** (0.268)
Income (more than $100,000 per year, %)	1.190** (0.294)	1.062** (0.290)
Region (urban area, %)	−0.382 (0.279)	0.108 (0.281)
Device usage control variables		
Device purchase price ($)	−0.414** (0.134)	−0.440** (0.132)
Voice traffic fees ($)	−0.070 (0.134)	0.106 (0.134)
Instances of text usage	−0.125 (0.139)	−0.146 (0.137)
Online Internet traffic fees ($)	1.410 (0.133)	1.300** (0.132)
Observations	2,492	2,492
R^2	0.188	0.214

Note. ** $p < 1\%$, * $p < 5\%$, and ( ) is standard error.

empirical model and estimating it using actual app download records of a consumer panel. Table 3 presents the coefficients of the comparative model, which differ from those of the app download model presented earlier. Model 1-2 in the table shows the results of the proposed app download formula. To determine the necessity of controlling the market environmental factors described above, we present Model 1-1 without the market environment variables for comparison. If the market environment is not considered, the temporal flow pattern of downloads may simply be compared between innovators and noninnovators. Despite its simplicity, however, this approach has the intrinsic limitation that it does not consider the effects of external factors such as the number of available apps and improved app market awareness.

We now interpret the results of Model 1-1 wherein the market environment is not controlled. Model 1-1 in Table 3 presents baseline values that are positive for both innovators ($\beta_0 = 2.146$) and noninnovators ($\beta_0 + \beta_1 = 2.146 + 4.578$). It is noticeable that the coefficient has a higher value in noninnovators than in innovators. This may be interpreted as a signal implying that, in the initial stages, noninnovators download more apps than innovators. However, innovators do not reduce their download behavior over time ($\beta_2 = 0.008$); on the other hand, a significant decrease in downloads is evident for noninnovators as they accumulate experience ($\beta_2 + \beta_3 = 0.008–0.464$). These results for Model 1-1 are almost the same as the download patterns for innovators and noninnovators in Figure 3. In the early days of adoption, noninnovators may download more apps; however, this gap is reduced as time passes. Overall, when we limit our focus to the results of Model 1-1, it seems that innovators may not be heavier app users than noninnovators. Nonetheless, this conclusion can be drawn from the analysis when we do not take into account external effects arising from changes in the market environment, such as increases in the number of attractive app products and market growth. Considering the restrictive nature of this model, we see that its results must be duly compared with those of Model 1-2, which incorporates control variables related to the market environment.

In Model 1-2, the market environment includes control variables. Model 1-2 is a practical model, useful for analyzing the download patterns of innovators and noninnovators. The estimation results of Model 1-2 may be summarized as follows. In Model 1-2, the coefficients corresponding to the baseline downloads of innovators and noninnovators are all nonsignificant (innovators $\beta_0 = -0.139$, noninnovators $\beta_0 + \beta_1 = -0.139–0.230$). In short, no significant differences in the number of monthly downloads are evident between innovators and noninnovators in the initial stage of market entry. By contrast, the results differ for download patterns after accumulated experience. Decreases in the number of downloads are evident for both kinds of consumers, but the proportional rate of decrease was far lower in innovators ($\beta_2 = -0.336$) in comparison with noninnovators ($\beta_2 + \beta_3 = -0.336–0.715$). That is, the number of downloads for both innovators and noninnovators is highest in the early days of app adoption, after which a gradual decrease occurs. In general, however, the decrease in the number of downloads is sharper for noninnovators (about 2.5 times that of innovators). From these results, we find evidence supporting the premise that innovators tend to download more apps than noninnovators over a long-time period. Accordingly, through the long-term analysis, it may be confirmed that innovators are heavier users than noninnovators in terms of the number of downloads.

The coefficient of calendar month is positive ($\beta_4 = 0.761$) in Model 1-2. This means that the number of downloads increased over time. A plausible cause may be found in Figure 2, which reveals an increase in the number of attractive apps available to consumers over time. Measurement of the effect of the market environment in Model 1-2 requires one condition: the changes in consumers' downloading behavior must be *linear*. However, the reality may be that changes in the market environment do not always occur in a regular pattern. It is necessary, therefore, to assume a *nonlinear* relationship between time

and the number of downloads [6] in an effort to reflect reality in the model. Therefore, we introduce a dummy variable representing the time factor on a monthly basis, creating an additional model. This proposed time variable is based on a time-varying, semiparametric model [17]. The advantages associated with usage of a dummy variable include the following: (1) the new model embodies nonlinear causal relations, (2) it enables us to estimate the causal relations at each time point independently, and (3) it provides a robustness check for comparison with the estimation results of Model 1-2. In comparing the results of both models, we include the control effects of exogenous factors and then compare the app download patterns between innovators and noninnovators in a more sophisticated way. The results from estimation using this additional model are as follows: (1) they reveal an exponential increase in app downloads at the later stage rather than at the initial stage, and yet (2) the main effects are not significantly different from those of Model 1-2.

In conclusion, given that the main effect remains almost the same regardless of the linearity or nonlinearity of the market environment and the number of consumer downloads, we adopt Model 1-2 as the final model since it is more parsimonious in structure. We now undertake an additional analysis to focus on differences in the download patterns in subcategories of apps. Utilizing the results of Model 1-2, we investigate their implications for the app market as a whole. App developers or development firms, however, may be more interested in what types of consumers will download their apps and how long they will continue to do so. Then, the starting question is how we can classify the myriad different kinds of apps?

In the current app market, various kinds of apps have been released and are available to consumers, including games, information search engines, social network services, and business utilities. In this study, we classify these apps into three groups: (1) games, (2) hobbies, and (3) information. The following are the underlying reasons for this classification. First, this classification is similar to the categorization in the app market. This practical approach to app classification relies on the categorizer focusing on the similarity between apps in terms of function or usage purpose. Relevant to this practical guide is the fact that the categorical share in the market of apps related to games, hobbies, and information remains at similar levels: 34%, 31%, and 35%, respectively. Second, on the consumer behavior level, classifying apps into three types is justified on the grounds that they may differ in terms of the procedures used for processing consumer-related information. Games are inherently intended to be used for pleasure [18]. The essential features of game apps include their colorful graphics and sounds, which give pleasure to players. In addition, rewards for achieving goals provide motivation to continue usage [19, 20]. By contrast, for apps in the information category, consumers choose them for practical purposes such as efficiency and economy. For apps in the hobby category, both categorical and utilitarian features are important. While using game apps provides pleasure, consumers deal with information through affective processes; when using information apps with utility traits, consumers engage cognitive processes. Likewise, apps must provide differentiated experiences to consumers. It is thus important to analyze consumer behavior with reference to categorical differences.

To analyze download patterns categorically, we extract three data sets, dividing all data according to the three categories described above. Next, using the same model structure as in Model 1-2, the three data sets may be analyzed. For example, we analyze only the records of downloaded games using the same variables as in Model 1-2. The results are represented by Models 2-1, 2-2, and 2-3 in Table 4. The interpretation of the estimation results may be summarized as follows. First, in the game category, innovators download more apps than noninnovators in the initial stage. No decrease in downloads between the two groups is found over time. That is, in the game category, innovators are always heavier users in comparison with noninnovators. Second, in the hobby and information categories, no difference in download behavior is evident between innovators and noninnovators at the initial stage; however, the degree of decrease for innovators is less than that for noninnovators over time. That is, in these categories, innovators are heavier users who download more and more apps over time. Thus, the analysis indicates that innovators are heavier users than noninnovators only in the two categories other than the game category.

As for the cause underlying these different patterns across the app categories, we postulate as follows. Innovativeness provokes the desire to explore new apps, and thus, innovators tend to download new apps periodically. The results of previous studies suggest that innovators acquire more professional knowledge about new products than their neighbors, thereby raising their social status [6, 10]. Accordingly, innovators have a greater desire to experience new apps in comparison with noninnovators. As a result, innovators download more apps on average than noninnovators in the long term. It is relevant that apps in the game category exhibit cyclical fluctuations, whereas those in the hobby and information categories are relatively free from such variation. Essentially, game apps provide the consumer with pleasure, and yet this pleasure lasts for a short time only, after which the app rapidly loses its effectiveness when usage reaches a certain level [18]. Inevitably, consumers pursue new pleasures through new game apps. As a result, download behavior in the game category is periodic, and the effect of innovativeness is minimal. On the other hand, in the case of hobby and information apps, consumers may continue using the same apps for a longer period if they provide utility. For example, in these two categories, consumers' needs are satisfied when they download apps with specific functions such as messaging, information searching, planning, and news. They have no need to download additional apps with the same functions. This characteristic of apps in the hobby and information categories results in a specific pattern whereby the number of downloads rapidly decreases over time. We therefore conclude that the number of downloads is less reduced for innovators than for

Table 4: Main results of the regression model 2: app category model.

Variables	Models by app categories		
	Model 2-1: game, apps	Model 2-2: hobby, apps	Model 2-3: information, apps
Intercept	0.289** (0.127)*	−0.137** (0.179)*	−0.097** (0.160)*
Noninnovator	−0.399** (0.186)*	0.068** (0.263)*	−0.174** (0.234)*
Months since adoption	−0.129** (0.022)*	−0.104** (0.027)*	−0.074** (0.024)*
Noninnovator × months since adoption	−0.013** (0.019)*	−0.173** (0.032)*	−0.179** (0.029)*
Calendar month	0.109** (0.020)*	0.190** (0.028)*	0.188** (0.025)*
Demographic control variables			
Age	−0.033 (0.033)	−0.188 (0.422)	0.087* (0.038)
Gender	−0.069 (0.065)	−0.276** (0.084)	−0.463** (0.076)
Income	0.236** (0.071)	0.297** (0.091)	0.150 (0.083)
Region (urban area)	0.033 (0.069)	−0.143 (0.088)	0.192* (0.080)
Device usage control variables			
Device purchase price ($)	0.007 (0.032)	−0.084* (0.041)	−0.130** (0.038)
Voice traffic fees ($)	0.064 (0.033)	0.101** (0.042)	−0.019 (0.038)
Instances of text usage	0.027 (0.033)	0.043 (0.043)	−0.111** (0.039)
Online Internet traffic fees ($)	0.147** (0.032)	0.434** (0.041)	0.206** (0.038)
Observations	2,492	2,492	2,492
R^2	0.032	0.094	0.082

Note. ** $p < 1\%$, * $p < 5\%$, and ( ) is standard error.

noninnovators since the former users are more actively searching for new apps.

5. Discussion

This study has some meaning for researchers. First, we targeted the app market, which has not yet been properly studied. While the recent exponential growth in this market has aroused widespread social interest, relatively few researchers have undertaken the task of directly observing and analyzing consumer behavior in this market. We collected actual download data at the consumer level in the app market, analyzed consumer download patterns, systematically considered consumer behavior in terms of mobile device usage, and examined the effects of demographic characteristics and the market environment. As a result, we found that various environmental factors should be considered for accurate understanding of consumer download patterns in this market.

In addition, this study provides useful parameters and models to measure variables pertinent to the app market and establishes helpful criteria to interpret the results. For example, in terms of the market lifecycle, the app market is leaving the initial stage and entering into the expansion phase, in which downloading behavior varies considerably. Second, the results of this study have expanded those of previous research on the direct relationship between innovativeness and heavy usage of new products [8] and have further applied the findings of previous studies to the online content market. Based on previous studies in the field of innovativeness theory, we have extended the discussion of opinion leadership and social status to the consumption and diffusion of mobile apps [6, 10]. In this theoretical framework, innovators were predicted to look for new products periodically; efforts were made in the current study to confirm this prediction and to empirically demonstrate the validity of the finding that innovators lead market growth [4] and have a crucial impact on both initial product distribution and long-term market performance [7].

The results of the model estimation and interpretation presented herein provide some practical implications to marketers and manufacturers of apps, as summarized below. First, practitioners must utilize knowledge of the behavior of innovators in the app market in the longer term from

a lifetime-value perspective. Due to their greater desire for new things, innovators tend to explore and download new apps periodically. They continue to download apps, and the cumulative number of apps downloaded increases over time. Hence, they tend to remain as customers for a longer period and have higher probability of downloading more apps on average than noninnovators. This behavior enhances their lifetime value for app companies [21]. Second, app companies should focus on the initial period of consumers' entry into the app market. The analysis results herein suggest that most downloading occurs in the early period, after which it gradually decreases. In the early period, consumers may do some basic research on their new mobile devices and explore the available apps. We also predict that consumers will continue using apps that were downloaded in the early period. Hence, the period during which the maximum revenue from downloading may be earned will be the initial period following consumers' entry into the market. Third, different target audiences can be identified according to different app categories. For game apps, companies should focus more intensively on innovators than on noninnovators both in the long and short term. For hobby and information apps, companies should target both innovators and noninnovators in the early stage but should focus on innovators in the long term. For game apps, the periodicity of downloading is similar in both groups; hence, companies should implement periodic recommendation programs targeted at both groups. Lastly, the number of app downloads must be generally increased in order to consolidate the maturity of the app market. The analysis results demonstrated that the average number of downloads tends to increase more rapidly as the market approaches maturity. Plenty of available alternatives in the market and improved convenience in searching for and selection of apps are critical factors in the efforts to increase the number of app downloads.

6. Conclusion

In this study, a comparative analysis was conducted to determine whether and how innovators are heavier users of apps in comparison with noninnovators. For this purpose, we classified the consumers in the pseudonym Goapps.com, a large app market, into innovators and noninnovators, collecting and analyzing data consisting of the number of apps downloaded at various points in time, information about mobile device usage, and demographic information. The results of the exploratory analysis provide no clear answer as to whether innovators do actually download more apps than noninnovators. On the contrary, noninnovators actually seem to download more apps than innovators in the early stages of app market development. In the analysis using a regression model capable of considering the market environment and other control factors, the results confirmed that innovators are significantly heavier users than noninnovators in the long term. The results have also demonstrated a basic trend wherein both groups do the most downloading in the early days of entry into the app market and then gradually reduce their downloading behaviors. After the turning point, a sharper decrease in downloads was evident for noninnovators compared to innovators.

In a further analysis, we compared the patterns of innovators and noninnovators in three app categories: games, hobbies, and information. In the game category, there was no difference in the patterns of decreasing downloads between innovators and noninnovators. By contrast, in the hobby and information categories, noninnovators showed a sharper decrease than innovators. The reason for this difference lies in the periodic nature of game apps, which induces consumers to download new products regardless of their level of innovativeness, whereas the hobby and information apps may not affect consumers' downloading behavior in quite the same way once their initial functional goals for app usage are fulfilled. In this circumstance, developers take advantage of the fact that innovators have an inherent tendency to pursue new things and thus are likely to continue exploring new apps even if their functional needs have been satisfied. This characteristic is indeed reflected in their behavior in the data described herein, in which periodic downloads of hobby and information apps occur. The results imply the necessity to take into account the market environment and categorical differences in the comparison of innovators and noninnovators.

In this study, the findings of previous studies on the innovativeness in the app market in the initial stage have been applied and empirically analyzed to prove that innovators may contribute to app market performance more than noninnovators. Despite these contributions, this study has certain limitations. First, we measured consumers' choices and predicted market performance from the app download perspective. Downloads may be interpreted as adoption of individual apps. In this study, we did not collect and utilize observations on how long consumers actually used the products. In the real app market, companies earn revenues from advertisement fees based on usage time. Hence, additional studies must be conducted to measure performance based on multiple performance variables, such as app usage frequency and usage time. Furthermore, through the exploration of the various variables, we may analyze many models of the app usage process simultaneously by applying standards such as time of entry into the app market, app adoption, and app usage time. Second, classification in this study was conducted at the category level; apps were classified into three types (games, hobbies, and information). It is possible, however, that characteristics of apps may differ within each category; hence, more detailed criteria for observation must be introduced. A previous study on the categorical structure and categorizing criteria [22] can provide a basis to ascertain new categories and types suitable for observation of heterogeneous consumer behaviors. Third, while we were not able to observe the effect of differences in app prices, the price effect can be analyzed in future studies. In the app market, price is one criterion crucial to consumer choice [9], determining the degree of consumer engagement and attitude. Through using the additional variable, the differences in download patterns between paid and free apps may be examined. Lastly, in the previous studies, the innovativeness

is measured by the internal and external [8, 11, 12] characteristics [3, 10, 13]. In this study, we divide the innovators and noninnovators using the purchase time. It would be useful to understand more comprehensive users' behavior in the multiple dimension of their characteristics.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This paper was supported by Chungnam National University in 2017.

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