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Determinants of growth and decline in mobile game diffusion☆

Jisu Yi, Youseok Lee, Sang-Hoon Kim*

Seoul National University, College of Business Administration, 1 Gwanak-ro, Gwanak-gu, Seoul 08826, Republic of Korea

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ABSTRACT

Rapidly advancing mobile technology has made mobile games a leader in the global games market. As the market size of mobile games has grown, the competition has also accelerated enormously. Thus, in order to ensure success, mobile games must sustain their initial boom for a long time, as well as attract enough users to solidify their installed base. The purpose of this research is to detect diffusion patterns and identify the determinants of mobile games' growth and decline hazards. The results show that mobile games have a distinctive brand-level life cycle in which the growth possibility decreases monotonically over time after the release, while the decline possibility rises after reaching the peak and then later begins to fall. This paper shows how the games' characteristics affect their attracting/holding power. The study provides implications for developers and distributors in terms of how to design, market, and manage mobile games.

1. Introduction

Rapidly advancing mobile technology has enabled virtually everything to happen in the palms of our hands. This revolution has also changed the global games market. Consumers no longer only rely to their PCs or consoles to play games. Instead, they have grown accustomed to using their hand-held smartphones or tablet PCs to enjoy an immersive gaming experience. Newzoo, a game consulting company, recently reported that the market share of mobile games has already overtaken that of PC and console games. The scale of the mobile games market is expected to reach $36.9 billion at the end of 2016, which is almost 37% of the whole market. The market share is predicted to grow up to 45% by 2019.[1]

As the market has grown enormously, many game developers have entered the market and have produced a tremendous number of games, which in turn has accelerated the competition. According to an online statistics company, Statista, the number of apps and games submitted per month for release on the iTunes App Store is increasing rapidly [from 3394 (Jan 2012) to 19,130 (Jan 2016)].[2] From this hard struggle for existence, the product life cycle of apps has decreased to 54.84 days as of 2012, which is much shorter than that of traditional product categories (Liu, Jia, & Guo, 2014). Thus, it is crucial for the success of game apps not only to form an initial installed base by attracting early adopters but also to extend their life span for as long as possible. In other words, different marketing strategies are necessary to manage mobile games along their product life cycle.

Although various studies in the field of marketing have explored the product life cycle, research on the life cycle of mobile games is scarce. The purpose of the current research is to explore the overall patterns of diffusion and the decline of mobile games, thereby achieving a better understanding of dynamics in the mobile game industry. This study also aims to identify the determinants of the growth and decline in the brand-level life cycle of mobile games. Overall, by examining the patterns and the determinants of the initial adoption, this study extends the research on mobile games' success.

This research also provides several implications in the context of computer games. Most prior studies related to games have concentrated on identifying the antecedents of consumers' category adoption through surveys and experiments. However, the present research attempts to understand the adoption of mobile games at a brand level rather than a category level. The brand level data were exploited to reveal the determinants of mobile game diffusion by focusing on the contents' attributes rather than the individuals' motivations. Further, our research expands the findings of previous literature on the success of games by examining the subordinate stagnation as well as the initial diffusion. This study may give various practical implications for game developers and distributors with respect to how to design, market, and manage mobile games.

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* Corresponding author.
E-mail address: profkim@snu.ac.kr (S.-H. Kim).

[1] “2016 Global Games Market Report: An Overview of Trends & Insights”, June 2016.

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2. Conceptualization

Research on games has been conducted in various disciplines. In the business related field, the topic has been investigated in two streams of research. On the one hand, some studies have tried to find explanatory factors of consumers' behavior toward games in terms of product categories (Bae, Koo, & Mattila, 2016; Chang, Lee, & Kim, 2006; Chang, Liu, & Chen, 2014; Ha, Yoon, & Choi, 2007; Hsiao & Chen, 2016; Huang & Hsieh, 2011; Wei & Lu, 2014). Chang et al. (2006) surveyed Korean online game users to reveal the effect of the users' innovativeness, perceived needs, and perceived popularity on adoption behavior. Huang and Hsieh (2011) adapted 'uses and gratification theory' and 'flow theory' to explain that gratifications and online experiences enhance customer loyalty toward online games. Ha et al. (2007) found that perceived ease of use, perceived enjoyment, and perceived attractiveness increase the intention of mobile game adoption. Hsiao and Chen (2016) identified that mobile game loyalty is formed by playfulness, access flexibility, connectedness, and reward.

On the other hand, some researchers have tried to build econometric models incorporating product-specific and market-specific variables to explain the financial performance of games (Burmester, Becker, van Heerde, & Clement, 2015; Gil & Warzynski, 2015; Marchand, Hennig-Thurau, & Wiertz, 2016; Oh & Min, 2015). Burmester et al. (2015) examined the impact of publicity and advertising through magazines on the number of video games sold. Gil and Warzynski (2015) suggested that exclusivity of a video game is associated with lower sales while vertical integration among developer, publisher and platform company is associated with higher sales. Marchand et al. (2016) focused on the different effects of consumer reviews and microblogs on video game sales while controlling for covariates such as advertising, pricing, and publishing strategy. Oh and Min (2015) tested the mediation effect of popularity ranking of mobile games on the relationship between advertising and in-app purchase sales by using actual expenditure and revenue data from a mobile game publisher in South Korea (hereafter, Korea). Because of the lack of data availability, research utilizing field data are rare in comparison to research with surveyed data. However, as the mobile application market has evolved, most app distribution channels publicly display the rankings of their bestselling apps. This study employs the ranking data of the Korean mobile games market in order to build a model that describes the product life cycle of mobile games.

Even though numerous studies have explored games as a research topic, none of them have dealt with its product life cycle. The length of the product life cycle (PLC) is defined as "the time between introduction and withdrawal from the marketplace" (Bayus, 1994). In the mobile games industry, most brands have short PLCs. There are several reasons for the short PLC in this industry. First, there exists fierce competition in the market. The number of new mobile games has grown dramatically in recent years. As this type of hedonic market constantly seeks new and updated products, users' interests also quickly shift to the newer products, inevitably leading to strong supply and demand dynamics (Clement, Fabel, & Schmidt-Stolting, 2006). Second, as 'free-to-play' models are commonplace, consumer's burden, in terms of time and monetary effort needed for a trial, becomes relatively small. Consumers can easily download, play, and later delete the mobile game of their choice at any time. Third, as the 'superstar or bomb' characteristic is commonly observed in the entertainment industry, only a few games survive for several months, while the vast majority of games disappear from the marketplace within a month.

The product life cycle consists of four stages: introduction, growth, maturity, and decline. Among the four stages, we specifically focus on the starting point of growth and decline stage within the product's diffusion process. The growth stage is defined as "the period from a new product's takeoff until its slowdown in sales," and the decline stage is defined as "the period of steadily decreasing sales until a product's demise" (Golder & Tellis, 2004). Although detecting the beginning of the decline stage is as important as that of the growth stage, the decline stage has rarely been the focus of research compared to the research on the introduction and growth stages (Marchand, 2016). To contribute to the insufficient literature in mobile game diffusion, we suggest a new framework encompassing the rise and fall of each mobile game. Here, we frame the concepts of *attracting power* and *holding power*. *Attracting power* refers to the ability to entice consumers in the introductory stage (Ahn & Kim, 2003). If a product has a higher attracting power, it can grow much faster right after its release. As a result, growth hazard, which is defined here as the possibility of successful diffusion in the early phases, will be high. *Holding power* refers to the ability to maintain the number of users over time (Ahn & Kim, 2003). A product with a higher holding power can enjoy long-term success and can continually appeal to new adopters. For this case, the decline hazard, which is defined here as the possibility of turning toward a decline phase, will be low. From the conceptualization above, we suggest the propositions below prior to our hypotheses.

Proposition 1. The stronger the attracting power is, the higher the growth hazard of a mobile game becomes.

Proposition 2. The stronger the holding power is, the lower the decline hazard of a mobile game becomes.

3. Hypotheses

3.1. Baseline hazard

The baseline hazard refers to the risk of an event's occurrence for individuals at the baseline levels of covariates. It is analogous to the intercept in a regression model in such a way that it serves as a reference value. In this study, the baseline growth hazard refers to the general possibility of successful diffusion for each mobile game, excluding the influence of explanatory covariates. We anticipate that the baseline growth hazard, which is measured by the games' reaching the upper ranks, is expected to peak right after a product's release, and then gradually decrease. When a product has a short life cycle, most marketing actions are concentrated on the period around the release date (Elberse & Eliashberg, 2003). Thus, new games can enjoy a period of maximized spotlight right after their release, but the spotlight effect disappears as time passes. The decreasing growth hazard is also related to the fierce competition in the market. In an overcrowded mobile app market, it is difficult for new apps to attain exposure, thus getting lost in the long tail before proving their value (Siegfried, Koch, & Benlian, 2015). Furthermore, since the users' interests quickly change from one app to another (Liu, Jia, et al., 2014), the possibility of reaching the upper ranks might be low once the game misses its chance during its early period. To this end, we expect that the growth hazard will monotonically decrease over time from the point of release.

H1. The growth hazard decreases over time monotonically.

The baseline decline hazard here refers to the general possibility of turning toward a decline phase for each mobile game, excluding the influence of explanatory covariates. Here, we clarify the decline hazard of a mobile game as the possibility of falling to the lower ranks. We expect that, once a game accomplishes reaching its highest rank, the decline hazard will decrease over time for the following reasons. Kretschmer, Klimis, and Choi (1999) argue that cultural products are under the influence of social contagion and increasing returns, due to the uncertainty of the products' quality and the self-enforcing feedbacks of the customers. Some research (Kim & Lee, 2013; Walls, 1997) has found empirical evidences of departure from Pareto's Law (Steindl, 1965; Zipf, 1965) in the relationship between firm size and rank, and has labeled this auto-correlated growth as increasing returns to information. Walls (1997) and Kim and Lee (2013) successively support that the rank-revenue relationship for movies departs from the Pareto distribution in ways to support auto-correlated growth. Giles (2007) supplies further results in the US popular music market concluding that contents that have enjoyed a recent boom are more favorable to stay at the top of the charts. This market concentration tends to increase when the information on demand becomes publicly available (Maecker, Grabenströer, Clement, & Heitmann, 2013). When the exposure in the top charts happens continuously, it can generate informational cascades (Golder & Tellis, 2004) causing long-lasting inflow of new adopters. From this mechanism, we anticipate that the possibility of approaching the decline phase is maximized at the point of reaching the peak, and then monotonically decreases over time.

H2. The decline hazard decreases over time monotonically.

3.2. Determinants of attracting power

For information goods, it is beneficial to have an installed base of significant size as early as possible (Kleijnen, De Ruyter, & Wetzels, 2004). As a means of attracting new adopters within a short time, game publishers strategically collaborate with mobile messenger services. In Korea, for instance, most games in the top sales ranking have been released through the top two mobile messenger platforms 'KakaoTalk' and 'Line'. Under the collaboration, game players voluntarily send invitation messages to their messenger friends in return for game items. In this way, linkage to a mobile messenger can create a network effect from its 'social function'. Jin, Chee, and Kim (2015) state that Korean mobile users are first exposed to new games through 'KakaoTalk' and this interaction within the social network results in viral success. Prior research on games has examined the impact of social influence on behavioral intention (Lu, Lin, & Lin, 2016), its influence on continuance intention (Chang et al., 2014), friend usage on installation intention (Siegfried et al., 2015; Wei & Lu, 2014), and social utility on continuance intention (Hsiao & Chen, 2016; Huang & Hsieh, 2011). To this end, we expect that a linkage to mobile messengers might affect the growth hazard positively.

H3-a. Linkage to a mobile messenger within a game increases the growth hazard.

Another possible determinant of attracting power is the scale of the marketing inputs. When consumers purchase experiential goods, they refer to the product information in order to resolve any doubts about their quality. Since the marketing activity from the provider is the only source of information during the early phases, this external information has a great effect on the initial success of the product. As a proxy for the marketing capacity of mobile games in general, we can think of the publisher's experiential ability. According to Cox (2014), blockbuster videogames are those released by one of the major publishers. Marchand et al. (2016) assume that video games published by one of the top ten biggest publishers would more easily achieve greater sales. In addition, Gil and Warzynski (2015) show that vertically integrated publishers are advantageous in that they have more revenue, can demand a higher price, and hold a greater market share than small publishers. Also, in the mobile application industry, app publishers who have previously launched similar types of mobile content can more easily utilize their accumulated knowledge to better promote their new apps. Siegfried et al. (2015) consider vendor reputation and the number of apps provided by the same vendor as potential determinants of app installation likelihood. Thus, we expect the publisher's power, in terms of its experiences in the industry, to be beneficial in shortening the duration in reaching the upper ranks.

H3-b. Publisher power increases the growth hazard.

Furthermore, as a promotional tool during the pre-release phase, app publishers often create online user communities. The official online community has its merit in that publishers can directly give promotional information to potential users. Moreover, the community can generate social interactions and enhance word-of-mouth (WOM) intention as well as increase brand identification (Kim, Park, & Kim, 2003; Lewis, Brown, & Billings, 2017; Li, Elliot, & Choi, 2010). Some research has concluded that this social interaction may enhance loyalty toward online games (Huang & Hsieh, 2011; Kim, Kim, & Mattila, 2012) and boost intention to play mobile games (Wei & Lu, 2014). Specifically, Hsiao and Chen (2016) measure connectedness as the 'benefit from the user community' to show its effect on mobile game loyalty and in-app purchase intention. From this evidence, the assumption on the effect of having an official online user community is hypothesized as follow.

H3-c. An official user community increases the growth hazard.

Content providers also make use of TV advertising. Advertising expenditures are typically a strong predictor of the product's success, since it can generate a marketing buzz (Marchand, 2016; Yoo & Kim, 2010). In game-related research, Marchand et al. (2016) incorporate pre- and post-release advertising expenses to show their positive impact on the video game sales. Burmester et al. (2015) provide further evidence of a causal relationship between advertisement and game sales. Oh and Min (2015) unveil the effect of advertisement on download rankings and on in-app purchase sales of mobile games. To this end, we hypothesize that TV advertisements might shorten the duration in reaching the upper ranks and reduce the growth hazard.

H3-d. TV advertisements increase the growth hazard.

Information accessibility is expected to be another important factor of early diffusion. Increasing the exposure of a newly released app is essential for survival under the fierce competition, and awareness is one of the most crucial factors for a game to be a hit (Park & Kim, 2013). To appeal to the potential users, enhancing the ease of discovering the specific app is also necessary (Song, Kim, Jones, Baker, & Chin, 2014). One way of increasing accessibility and discoverability is to release the app into as many markets as possible. It is found that the performance of a game grows as the number of platforms increases (Marchand, 2016). Bresnahan, Orsini, and Yin (2014) develop a model on the platform choice by mobile app developers and identify strong incentives for most apps to multihome (releasing both on iOS and Android). Marchand et al. (2016) posits that the number of platforms in which the video game was released in may increase unit sales. Furthermore, Gil and Warzynski (2015) display that platform exclusivity has a negative impact on video game sales and revenues. Thus, the expectation on the effect of the number of app markets is hypothesized.

H3-e. The number of app markets in which the game is released in increases the growth hazard.

Another way to promote a game is to utilize the recommendation function provided by app platforms. Google Play, the largest mobile app platform, features a selection of games to its visitors on the front page of its games category section. Being listed on this page can dramatically increase the viewers' awareness and chance of trial of the recommended games through increased perceived attractiveness and perceived popularity. Ha et al. (2007) prove the impact of perceived attractiveness on the attitude toward playing mobile games. Chang et al. (2006) examine the effect of perceived popularity on online game adoption. Thus, we expect that the number of app markets and the number of opportunities to be featured by the market platform can shorten the time span for a game to reach the upper ranks.

H3-f. The number of times a game is featured increases the growth hazard.

3.3. Determinants of holding power

The adoptions of games in the late phases are decided more by internal influences than external influences (Bass, 1969). For late adopters, subjective information, such as WOM and reviews, tends to be

Table 1
Functional forms of survival models.

Distribution	Survival function $S(t\|X)$	Hazard function $h(t\|X)$	Parameterization	Ancillary parameter
Exponential	$\exp(-\lambda t)$	λ	$\lambda = \exp(X\beta)$	–
Gompertz	$\exp\{-\lambda\gamma^{-1}(e^{\gamma t}-1)\}$	$\exp(\gamma t)\lambda$	$\lambda = \exp(X\beta)$	γ
Lognormal	$1-\Phi((\log(t)-\mu)/\sigma)$	$\frac{\phi(\log(t)-\mu)(\sigma t)^{-1}}{1-\Phi((\log(t)-\mu)/\sigma)}$	$\mu = X\beta$	σ
G.G.	$1-I(\gamma,u)$	$\frac{\gamma^{\gamma}(\sigma t\sqrt{\gamma}\Gamma(\gamma))^{-1}\bullet\exp(z\sqrt{\gamma}-u)}{1-I(\gamma,u)}$	$\mu = X\beta$	σ,κ

Note 1: Mathematical form was adapted from Cleves, Gould, Gutierrez, and Marchenko (2010).
Note 2: X is the row vector of covariates (i.e., determinants of growth and decline hazard) and β is a corresponding column vector of coefficients.
Note 3: $\Phi(\cdot)$ and $\phi(\cdot)$ are the standard normal c.d.f. and p.d.f.
Note 4: $\gamma = \kappa^{-2}$, $z = \frac{\log(t)-\mu}{\sigma}$, $u = \gamma\bullet\exp(\kappa z)$, and $I(\cdot)$ is the incomplete gamma function.

Table 2
Measurement descriptions.

Variable	Measurement	Source
Growth-duration	The number of days for a game to reach the top 20 in the Google Play game download chart.	Appannie.com
Growth-censored	Whether a game reached the top 20 (dummy variable).	Appannie.com
Decline-duration	The number of days for a game to go down 10 ranks within 3 consecutive days from the highest rank of a game.	Appannie.com
Decline-censored	Whether a game experienced downturn (dummy variable).	Appannie.com
Messenger linkage	Whether a game has a linkage to the mobile messenger 'KakaoTalk' (dummy variable).	Appannie.com
Publisher power	The number of game apps released by the publisher of a mobile game.	Appannie.com
Official community	Whether a game has an official online community managed by the publisher (dummy variable).	Hungryapp.co.kr
TV ad	Whether a game has an official TV advertisement (dummy variable).	Appannie.com, Google.com
No. of app market	The number of mobile platforms (app markets) in which a game is released.	Gevolution.co.kr
Early user satisfaction	The multiplied value of the number of favorable ratings and their average score of a game during a period of 8 days after release (in thousand).	Appannie.com
Early user dissatisfaction	The multiplied value of the number of unfavorable ratings and their average score of a game during a period of the first 8 days after release (in thousands).	Appannie.com
User satisfaction	The multiplied value of the number of favorable ratings and their average score of a game during a period of 39 days after release (in thousands).	Appannie.com
User dissatisfaction	The multiplied value of the number of unfavorable ratings and their average score of a game during a period of 39 days after release (in thousands).	Appannie.com
Early featured	The number of featured records of a game on the Google Play home page and in the mobile Google Play during a period of 8 days after release.	Appannie.com
Highest rank	The highest rank of a game during a period of a month after release.	Appannie.com
App size	Size of a game app (in megabytes).	Appannie.com
Rating	Content rating of a game app, '1' for 'teen' and 'mature' and '0' for others.	Appannie.com

more influential than objective information, such as product attributes (Cooper-Martin, 1992). This phenomenon is strengthened in the later phases of the life cycle because promotion is not the only source of information as more people experience the product (Ahn & Kim, 2003). The power of subjective information is also related to the fact that there are more risk averters in the later periods. These (potential) adopters tend to refer to others' opinions before making their own purchase decisions. In the context of mobile games, linkage with mobile messengers can play the role of social influence. Receiving invitation messages through a mobile messenger can inform potential users that many friends in his or her social network are playing the game, and thus, signal the popularity of the game in general. Also, in Marchand (2016), the social interaction feature was found to contribute to the sales of video games at the late stage of the product life cycle.

H4-a. Linkage to a mobile messenger decreases the decline hazard.

Similarly, the evaluations of earlier adopters can also directly affect the game's success in the later phases. It has been identified that consumer reviews and the number of ratings have a positive impact on purchase intentions (Hahn & Kim, 2013; Wang & Wang, 2010) and the number of mobile app downloads (Lee & Raghu, 2014; Liang, Li, Yang, & Wang, 2015; Liu, Au, & Choi, 2014; Son, 2017). Moreover, the players' evaluations are found to be one of the most significant factors in video game success (Cox, 2014; Marchand et al., 2016). To this end, we expect that users' evaluations will influence diffusion success in the later phases, and as a result, have an impact on the duration of staying in the upper ranks. We specifically divide users' evaluations into positive and negative WOM, following previous literature on the influence of review's valence (Lim & Chung, 2011; Liu, 2006). We anticipate that positive WOM will reduce the decline hazard, while negative WOM will accelerate the decline hazard.

H4-b. Users' satisfaction level decreases the decline hazard.

H4-c. Users' dissatisfaction level increases the decline hazard.

Moreover, the high ranking of a game is also expected to affect the possibility of decline hazards. Basically, a higher ranking position can boost demand, since it can guarantee high visibility in the app markets (Ifrach and Johari, 2014). Liu, Au, et al. (2014) measure product visibility by the app rankings, on the basis that the high ranking generates high level of awareness and interest. Carare (2012) develop a model to explain the causal effect of public ranking information on mobile app demand. There is evidence that the debut rank is an important marker for the long-term success of music albums (Bhattacharjee, Gopal, Lertwachara, Marsden, & Telang, 2007). Higher ranking is also associated with a larger installed base. Marchand (2016) found that a large installed base can induce higher video game sales during the later life cycle phase. To this end, we anticipate that the higher peak ranking achieved by a game is, the more people will try to play the game even during the later phases, thus reducing the decline hazard.

H4-d. The highest ranking of a game decreases the decline hazard.

Table 3
Descriptive statistics and correlations.

Variable	Mean (std. Dev)	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Growth-duration	4.12 (4.43)														
2. Decline-duration	15.68 (14.39)	−0.316***													
3. Messenger linkage	33 (37.9%)	−0.342**	0.298**												
4. Publisher power	46.84 (50.88)	0.01	−0.019	−0.135											
5. Official community	65 (74.7%)	−0.385**	−0.064	0.019	0.147										
6. TV ad^2	52 (59.8%)	−0.171	0.065	−0.18	−0.068	0.224*									
7. No. of app markets	1.75 (0.88)	−0.349**	0.051	0.009	−0.293**	0.286**	0.111								
8. Early dissatisfaction	13.56 (17.90)	−0.256*	0.208	−0.065	0.047	0.037	0.07	−0.189							
9. Early satisfaction	1.23 (1.43)	−0.168	0.16	0.061	0.107	0.071	−0.038	−0.104	0.546**						
10. Dissatisfaction	3.87 (5.25)	−0.278**	0.459**	0.047	0.101	0.159	0.057	−0.144	0.771**	0.402**					
11. Satisfaction	37.45 (58.82)	−0.196	0.356**	0.223*	0.15	0.084	−0.119	−0.09	0.436**	0.792**	0.577**				
12. Early featured	0.32 (0.98)	−0.137	−0.005	−0.233*	0.014	0.029	0.03	0.028	0.029	−0.009	0.099	−0.063			
13. Highest rank	14.95 (39.00)	0.718**	−0.247*	−0.240*	−0.088	−0.280**	−0.204	−0.294**	−0.223*	−0.153	−0.217*	−0.169	−0.102		
14. App size	51.87 (54.13)	0.134	0.115	−0.042	0.148	−0.043	0.183	−0.037	−0.095	−0.098	−0.091	−0.088	0.054	0.054	
15. Rating	44 (50.6%)	0.182	−0.156	−0.412**	−0.125	0.112	0.033	0.056	−0.02	−0.019	0.036	0.008	−0.004	0.042	−0.005

Note 1: The numbers of '1' (shares) were reported for the dummy variables.
Note 2: Calculating the mean and the standard deviation of the Growth-duration (Decline-duration), games that did not experience growth hazards (decline hazards) were excluded.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

4. Method

4.1. Hazard model approach

The current study uses the hazard model approach to test the hypotheses regarding the diffusion patterns and the role of content features. Many previous studies in the business field have applied the hazard model to examine the survival of firms, products and innovation adoptions (Kim & Park, 2011; Lee & Raghu, 2014). In this study, growth and decline duration of some games might not be observable because those games simply did not experience the events within the duration of the study. For these cases, a "right-censoring" problem occurs from the nature of incomplete observations. However, the hazard model analysis can deal with such censoring problem. In our model, durations to the growth hazard and the decline hazard are viewed as random variables that follow a probability density function $f(t)$ and a cumulative density function $F(t)$. The survival function $S(t)$ is defined as $1\text{-}F(t)$, which indicates the probability that the duration is at least t. The hazard rate, which is the conditional likelihood of the event's occurrence, is defined as $h(t) \equiv f(t) / [1\text{-}F(t)] = f(t) / S(t)$.

The hazard rate can be divided into two parts: the underlying baseline hazard and the effect of explanatory covariates. The former part describes the reference-level risk without the influence of covariates, while the latter part describes how the risk varies in response to the covariates. Depending on the assumption in the functional form, different parametric models are applicable. In characterizing the pattern of the baseline hazard, we considered four models as candidates: Exponential (for flat hazard), Gompertz (for monotonic increasing or decreasing hazard), Lognormal, and Generalized Gamma (for flexible non-monotonic hazard). Functional forms of estimation models are summarized in Table 1.

4.2. Sample and measurements

Our sample was collected among Korean domestic mobile games. The Asia-Pacific region has led the global mobile games market, generating 58% of the growth in the total market. Korea, the third largest market in this region, has generated revenues of 4047.3 million USD, and is ranked in the world's top four countries in its game revenues (Newzoo, 2016). Considering that Android OS has the largest share in the Korean smartphone platform, we referred to the download rankings based on Google Play. The initial sample frame consisted of 100 games from the top 100 chart of Google Play on October 1, 2015. We collected the daily download rankings of individual games of the first 90 days of games' release. Among the 100 games, 87 games were included in the final sample as 13 games were excluded due to the unavailability of the ranking data.

'Growth-duration' was measured by the elapsed days from the game's release to reaching the top 20 on the Google Play game download chart. Out of the 87 games, 75 (86.21%) reached the top 20 during our study period. Twelve games (13.79%) did not reach the top 20 by the end of study, and thus considered right-censored.[3] The variable "Growth-censored" indicates whether a game is (right-) censored. 'Decline-duration' was measured by the elapsed days from the date of the game's highest rank to the date of when the download rankings went down > 10 ranks within 3 consecutive days. During the study period, 62 (71.26%) experienced decline events, 9 (10.34%) did not experience any downturns (right-censoring),[4] and 16 (18.39%) experienced

[3] In regard to growth-duration, none of the sample were left-censored since the database tracked the games' ranks from their release dates. We did not count the cases of interval censoring (i.e., reaching the top 20 and then being dropped out) because those games should be still regarded as having achieved early phase success from hitting the top 20.

[4] Since our data set included the information of when the games reached the highest rank during the study period, none of the games were left-censored.

Table 4
Results of growth hazard model analysis.

Variables	Estimated coefficient (standard error)			
	Model 1 exponential	Model 2 gompertz	Model 3 log-normal	Model 4 generalized gamma
Messenger linkage	1.972(0.308)***	**1.395(0.316)*****	1.843(0.296)***	2.561(0.413)***
Publisher power	0.007(0.003)**	**0.004(0.003)**	0.004(0.003)	0.008(0.004)*
Official community	0.633(0.336)$^{+}$	**0.336(0.335)**	0.459(0.312)	0.518(0.462)
TV ad	0.717(0.274)**	**0.531(0.271)***	0.728(0.261)**	0.962(0.369)**
No. of app markets	0.796(0.164)***	**0.468(0.166)****	0.584(0.155)***	0.826(0.225)***
Early satisfaction	0.572(0.104)***	**0.403(0.105)*****	0.484(0.101)***	0.814(0.142)***
Early dissatisfaction	− 0.013(0.008)	**− 0.010(0.008)**	− 0.010(0.008)	− 0.025(0.011)*
Early featured	0.457(0.127)***	**0.299(0.122)***	0.385(0.123)**	0.546(0.163)**
App size	− 0.006(0.003)*	**− 0.003(0.003)**	− 0.003(0.002)	− 0.003(0.002)
Rating	0.310(0.273)	**0.306(0.270)**	0.272(0.272)	0.554(0.361)
Gamma	–	**− 0.062(0.018)**	–	–
Sigma	–	–	1.071(0.091)	1.367(0.185)
Kappa	–	–	–	0.698(0.421)
$\chi^2(10)$	178.36***	**48.53*****	67.59***	53.58*
Log likelihood	− 125.873	**− 113.654**	− 124.024	− 128.266
AIC	**273.746**	**251.309**	**272.048**	**282.533**

$^{+}$ $p < 0.10$.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

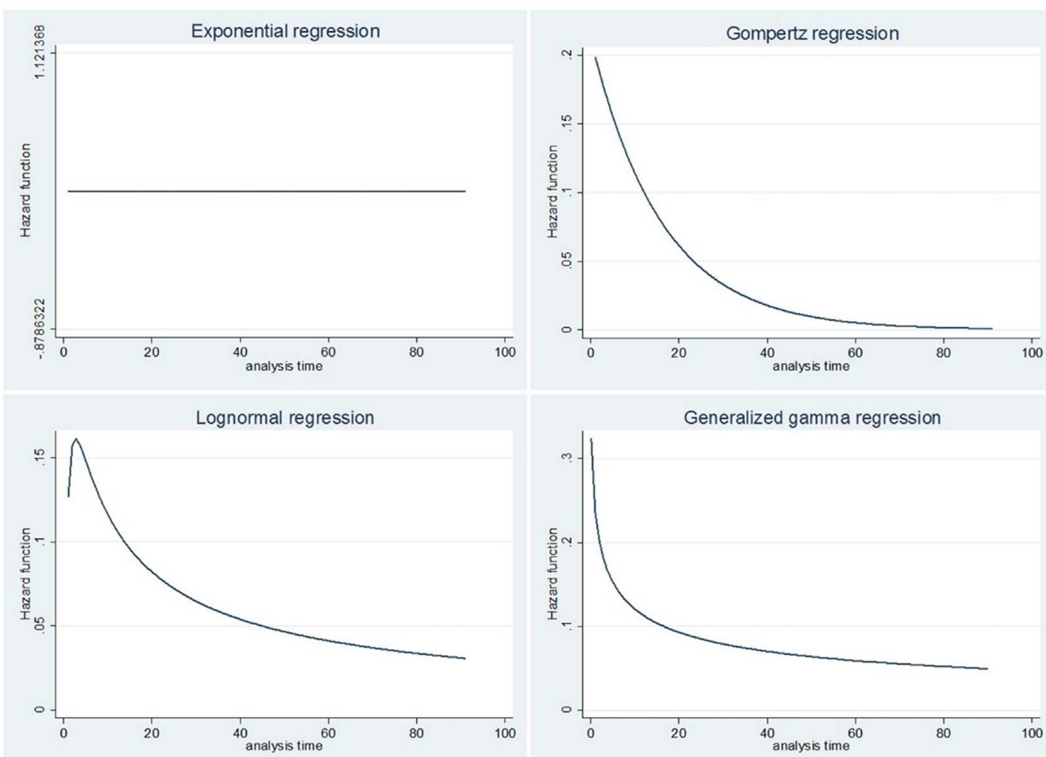

Fig. 1. Plots of estimated growth hazard function: (a) Exponential model, (b) Gompertz model, (c) Lognormal model, and (d) Generalized gamma model.

decline events but rebounded to their original rankings before the downturn (interval censoring).[5] The variable 'Decline-censored' indicates whether a game is censored.

We measured the 'Messenger linkage' as a dummy indicator: 1 if a game is linked to the mobile messenger 'KakaoTalk' (the largest mobile messenger service in Korea with > 90% of the market share and 48 million monthly active users), and 0 if no linkage exists. 'Publisher power' was measured by the number of previous games released by the publisher. 'No. of app market' was measured by the number of mobile platforms in which a game is released. Measuring users' evaluations, we partitioned the reviews into the early- and late-phase periods for the growth hazard and the decline hazard. In our sample, the average durations from the release to the growth hazard and the decline hazard were 8.24 days and 39.01 days, respectively. Depending on the values, 8 days and 39 days from the release were used in collecting early- and late-phase users' evaluations. We categorized the ratings into two groups: 'satisfied' for four- or five-star ratings and 'dissatisfied' for one- or two-star ratings (Chevalier & Mayzlin, 2006). Then, we measured

[5] We highly appreciate the reviewer's comments with suggestions to consider the cases of interval censoring.

Table 5
Results of the Decline hazard model analysis.

Variables	Estimated coefficient (standard error)			
	Model 1 exponential	Model 2 gompertz	Model 3 log-normal	Model 4 generalized gamma
Messenger linkage	− 0.609(0.300)*	− 0.579(0.309)+	− 0.422(0.246)+	− 0.151(0.289)
Publisher power	0.004(0.003)	0.004(0.003)	0.003(0.003)	0.003(0.003)
Official community	0.242(0.350)	0.204(0.352)	0.192(0.291)	0.162(0.293)
TV ad	0.246(0.293)	0.249(0.292)	0.231(0.256)	0.277(0.266)
No. of app markets	− 0.333(0.182)+	− 0.316(0.183)+	− 0.266(0.153)+	− 0.250(0.153)
Satisfaction	− 0.092(0.035)**	− 0.086(0.035)*	− 0.090(0.029)**	− 0.085(0.030)**
Dissatisfaction	− 0.004(0.003)	− 0.004(0.004)	− 0.003(0.003)	− 0.004(0.003)
Highest rank	0.009(0.003)**	0.009(0.003)**	0.009(0.003)**	0.009(0.003)*
App size	− 0.004(0.003)	− 0.004(0.003)	− 0.003(0.002)	− 0.003(0.002)
Rating	0.618(0.333)+	0.587(0.332)+	0.464(0.256)+	0.464(0.245)+
Gamma	–	− 0.006(0.008)	–	–
Sigma	–	–	0.955(0.089)	0.963(0.089)
Kappa	–	–	–	− 0.461(0.396)
$\chi^2(10)$	49.37***	37.06***	45.03***	41.69***
Log likelihood	− 108.969	− 108.723	− 102.448	− 101.792
AIC	239.938	241.446	228.896	229.584

+ $p < 0.10$.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

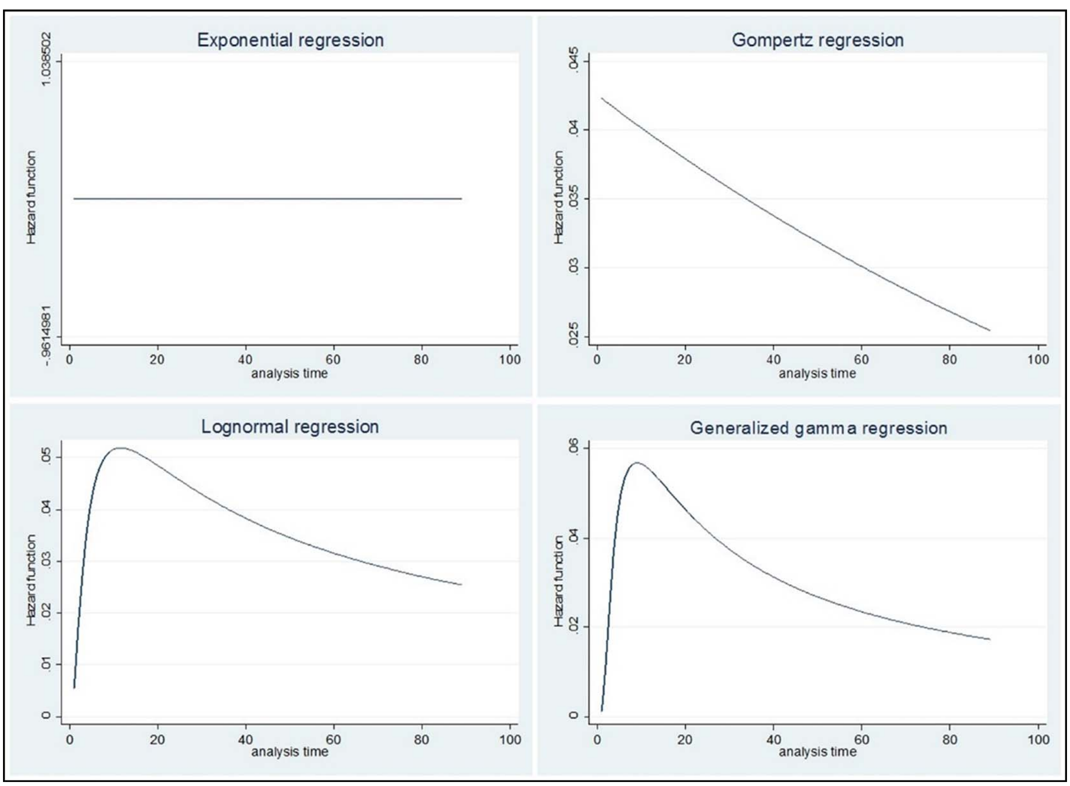

Fig. 2. Plots of estimated decline hazard function: (a) Exponential model, (b) Gompertz model, (c) Lognormal model, and (d) Generalized gamma model.

'Early user satisfaction (dissatisfaction)' by the multiplied value of the number of 'favorable (unfavorable)' ratings and their average star scores during a period of 8 days after release. We then similarly measured 'User satisfaction (dissatisfaction)' by the multiplied value of the number of 'satisfied (dissatisfied)' ratings and their average star scores during a period of 39 days after release. Next, 'Early featured' was measured by the number of featured records of a game on the Google Play during a period of 8 days after release. 'Highest rank' was measured by the peak ranking of a game within our study period. Lastly, we included two types of control variables: 'App size' and 'Rating'. Descriptions of the measurements and summary statistics are shown in Tables 2 and 3.

5. Results

5.1. Baseline hazard

We used Stata11 software to estimate the eight parametric models via maximum likelihood. Table 4 shows the estimation results of the growth hazard model. The models with different assumptions show

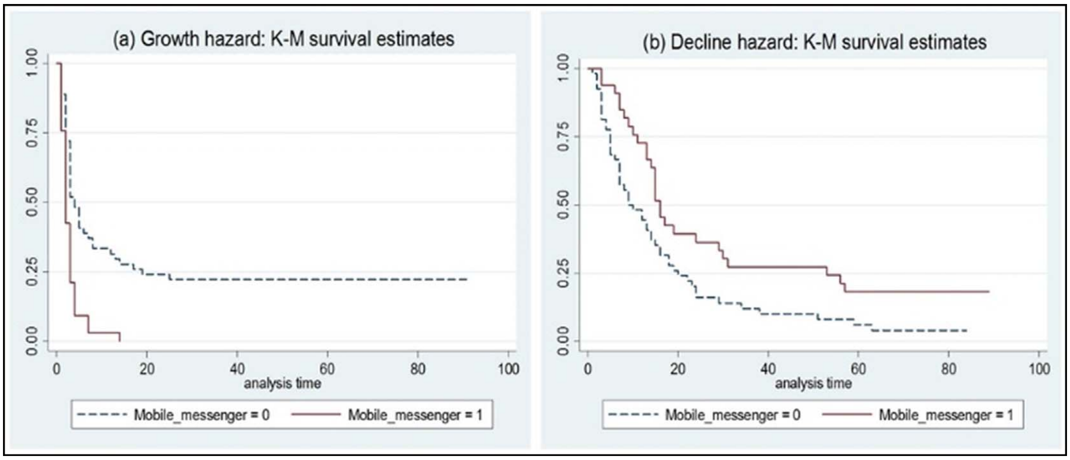

Fig. 3. Influence of linkage to mobile messenger: (a) Growth hazard; and (b) Decline hazard.

significant chi-square values, meaning that at least one coefficient is different from zero in all models ($p < 0.05$). Selecting the preferred model, we referred to the Akaike information criterion (AIC) values for model parsimony. Although the generalized gamma has the lowest log-likelihood, the gompertz (model 2) is more preferred, based on minimizing the AIC. The shape parameter of the gompertz model, γ, is estimated by the negative and significant value ($\gamma = -0.062$, $p < 0.001$), which supports the decreasing pattern of the growth hazard. Fig. 1(b) also demonstrates the monotonically decreasing pattern of the estimated hazard in model 2. Interestingly, even the generalized gamma distribution (model 4), which allows for the most flexible pattern, was found to shape the monotonic decreasing pattern, as well. From these results, we conclude that the growth hazard decreases over time monotonically, and thus H1 was supported.

The estimated results for the decline hazard models are shown in Table 5. The dependent variable is well explained by the app features in all models (i.e., χ^2 values are all significant under $\alpha = 0.001$). Here, the lognormal distribution (model 3) is chosen as the preferred model from its lowest AIC value. The significant estimate of the shape parameter confirms the non-monotonic pattern ($\sigma = 0.955$, $p < 0.01$). The higher value of the shape parameter in the lognormal distribution is associated with the earlier highest point in the hazard function. Fig. 2(c) illustrates the estimated hazard pattern for model 3, which rises at first and then begins to decrease at some point. Here, Fig. 2(d) of model 4, the result from the most flexible model, also shows a similar pattern of first increasing and then decreasing. Thus, the initial expectation of the monotonic decreasing decline hazards, H2, was not supported.

5.2. Determinants of attracting power and holding power

Model 2 in Table 4 shows the effect of mobile game attributes to the growth hazard, based on the preferred model (i.e., the gompertz distribution). Supporting H3-a, the results indicate that the growth hazard increases when a game has a linkage to a mobile messenger ($\beta = 1.395$, $p < 0.001$). In other words, a game with a messenger linkage tends to have higher attracting power and reach the top 20 earlier. The result also supports H3-d, in that having an official TV advertisement increases the growth hazard of a game ($\beta = 0.531, p < 0.05$). As for H3-e, the number of app markets is found to have a significant influence in increasing the possibility to reach the top 20 ($\beta = 0.468$, $p < 0.01$). Lastly, supporting H3-f, the more a game has been featured on Google play, the higher the growth hazard becomes ($\beta = 0.299, p < 0.05$).

The roles of game attributes on decline hazards were investigated, based on the estimation results of model 3 (lognormal distribution) in Table 5. The influences of messenger linkage (H4-a) was marginally significant ($\beta = -0.422$, $p = 0.09$), and supporting H4-b, users' satisfaction levels were found to reduce the decline hazard ($\beta = -0.090, p < 0.01$). In other words, the possibility of downturn is mitigated when a mobile game collaborates with a mobile messenger and holds numerous positive reviews. As for H4-d, the influence of the highest rank was also significant ($\beta = 0.009$, $p < 0.01$), meaning that games that reached a higher peak rank showed higher holding power. Contrary to our expectation, the influences of users' dissatisfaction levels (H4-c) were not statistically significant ($\beta = -0.003$, $p = 0.24$).

6. Discussion

This study shows that mobile games have a distinctive brand-level life cycle in which the growth hazard monotonically decreases over time after release, while the decline hazard rises after the peak and then begins to decrease. This paper also shows how the characteristics of games affect both the attracting and holding power.

First, the results of this study reveal that the probability of a game reaching the upper ranks (top 20) decreases as time goes by. This implies that the market potential of a newly released game is the highest right after its entry; yet, its marketability declines over time. The reason that fresh games have the greatest market power at their introductory phase is because mobile game distributors allot most of their marketing resources immediately after the release to maximize the awareness level of their products. Since numerous state-of-the-art games are released with the strong marketing support, existing games cannot be singled out among them. Besides, the trend of launching games as free-to-play not only encourage gamers to try out new content, which assists distributors in generating an initial installed base, but also makes it hard for games to achieve belated success without a boom at the outset.

Second, this research has also discovered that the possibility of a game turning toward a downturn (losing > 10 ranks within three days) from its peak increases for a short period of time before reducing continuously. This finding slightly differs from the hypothesis in terms of the decline hazard quickly inflating for a few days right after reaching the peak. This finding suggests that a game at the top of the chart can defend its position for a short time; yet, the chances of losing its place increases rapidly. However, when a game can keep its position for a certain period of time, the chances of holding the top spot increase constantly. The probability of a game turning toward a downturn rapidly goes up after reaching its peak ranking, because the substitution effect dominates the increasing returns to information in the short run. As the pattern of the growth hazard shows, even though most games achieve their highest rank immediately after being launched, most of them fall behind in the competition and deliver their position to new games. However, when a game holds its place for days without being substituted, a phenomenon called informational cascades, where consumers seek out the hit products, emerges. This leads to the phenomenon of a few blockbusters dominating the chart for a long time. For example, half of the top 10 mobile games (as of July 2016, Google Play, South Korea) have survived on the chart for longer than six months.

Third, through hypotheses testing, the present research confirms several factors that boost the attracting power of mobile games, such as having a linkage with a mobile messenger, being advertised on TV, the number of app markets in which the games are released, and the number of features on Google Play. Games that are linked with a mobile messenger can more easily entice new adopters by incentivizing current users to invite their messenger friends. When a game is advertised on TV, the awareness level of the game increases immensely, which in turn, brings additional newcomers. Releasing a game in various app markets can help attract more customers by tapping into the different group of potential customers in each app market. When a game is featured in the front page of app markets with the label 'Global Favorites' or 'Browse the Best', the possibility of users trying out the game is expected to escalate.[6]

Fourth, the analysis results also delineate which factors may enhance the holding power of mobile games. Again, the game's linkage with a mobile messenger has a negative effect on the decline hazard, which indicates a positive impact on the holding power. The network effect arising from the installed base of the mobile messenger strengthens exponentially as the number of users increases. Thus, the existence of a connection can help a game stay in the upper ranks for a longer time. In addition, the high satisfaction level of other consumers may reduce the uncertainty related to the game's quality, which encourages a continuous flow of new users and higher rankings. The highest ranking of a game also has a positive influence on its holding power. When the peak ranking of a game goes up, the visibility and the effect of the information cascades increase as well. In this fashion, a higher ranking itself can enhance the holding power of a game.[7]

The authors also attempted to examine the effect of mobile messenger linkage by applying the Kaplan-Meier survival analysis. Among the various significant variables, having a linkage with a mobile messenger was selected because it had a significant impact on the attracting and holding power. Fig. 3 shows the estimated distributions for the growth hazard and the decline hazard. When a game is connected to a mobile messenger, the growth hazard is greater and sustains for a longer time compared to that of games without any mobile messenger linkage. Also, the decline hazard of a connected game is smaller than that of an independent game. This result reconfirms our finding that mobile messenger linkage may intensify the attracting power and the holding power of a game.

7. Conclusions

This research entails several theoretical implications for understanding the diffusion patterns of mobile games and their determinants. First, the research endeavors to understand the adoption of mobile games at a brand level rather than a category level. Most prior research related to mobile games have focused on finding the antecedents of consumers' category adoption through surveys or experiments. The current research exploits brand level data and finds the determinants of mobile game diffusion focused on the contents' attributes rather than individuals' motivations. Second, the authors expand the literature on game success by examining not only initial diffusion, but also subordinate stagnation. This study demonstrates the distributions of the early-phase growth hazard and the late-phase decline hazard. The results reveal that different determining factors exist for early attracting power and late holding power. This explains that the introductory success of market penetration does not guarantee continued success along the life cycle. Third, this study applies a hazard model, which has rarely been used in the product diffusion literature and considers several distribution assumptions for the baseline hazard. This approach enables us to test the hypotheses on the shape of the growth hazard and the decline hazard, and to simplify the complex life cycle of a game with the two significant events.

This study also provides a handful of practical implications for game developers and distributors with respect to how to design, market, and manage mobile games. First, it is crucial to lift a game up to the upper rankings as soon as possible after the game is released, since the market value of a game diminishes rapidly as new competitors enter. To make this initial success, game developers should impose a linkage with a mobile messenger holding a large-scale user network. Even though forming a connection with a mobile messenger requires sharing revenues with the operator, the decisive growth it can provide in reaching the top charts after the game's release is critically beneficial. Moreover, early satisfaction level is another compelling factor that can determine the game's initial growth, and thus, the launching version of the games must have alluring elements to satisfy the early adopters. Also, distributors should allocate marketing resources for TV commercials and for securing multiple retail channels. Moreover, distributors should make efforts to figure out how to feature their game on the front page of app markets during the early phase. Second, it is also imperative to maintain a game at the upper rankings for as long as possible after the game has reached its peak, since its chances of becoming a blockbuster game increases significantly as the holding time of high rankings lengthens. To aid in this long-term success, developers are urged to link their game to a messenger service and to pursue high satisfaction ratings during the primary stage. After a couple of weeks into the game's release when both early adopters and majority users make up the user base, frequent updates are essential to boost the satisfaction level of the diverse consumer groups. Distributors should also be responsible for securing multiple distribution channels if possible and for maximizing the game's peak ranking position. When games reach the top charts, marketers should intensify their promotional activities to defend the position and to also challenge the higher ranked games.

In spite of contributions, the present research has some limitations. First, the download rankings might not exactly conform to the actual diffusion of the games. Although all app markets, including Google Play, have their own rankings calculation methods in consideration of several factors, the specific algorithm is confidential. Moreover, the download rankings cannot be free from autocorrelations since higher ranks induce more downloads. To overcome this problem, another methodology, such as quantile regression that segregates the entities, needs to be applied. Second, since most mobile games are released as free-to-play, the download records cannot explain the actual performance of games, and the results of the research hardly give insights into the perspective of revenues or return on investment. Future research could examine the financial success of game contents based on actual revenue data, if available. Last, although not covered in this study, online advertising via social media has recently been regarded to accelerate the diffusions of mobile games. Publishers diversify their advertising platform by simultaneously engaging in online advertising, TV advertising, and messenger service linkage to expand the installed base as fast as possible. Future research examining the roles of various marketing platforms could enrich the research stream of the mobile game diffusion.

[6] The results are restricted to the definition of the growth event. The authors conducted post hoc analyses under different definitions of growth-duration: reaching the top 10/top 15/top 25/and top 30. The results indicate that the significance of coefficients is unchanged. The specifications of the results are available upon request to the authors via e-mail.

[7] The authors conducted post hoc analyses under different definitions of the decline event: the download rankings going down > 10 (15 or 20) ranks within five (three) consecutive days from the date of the highest rank, or exiting the top 200, which is the featured limit on the Google Play webpage. The results show a similar pattern in terms of coefficients significance. The sensitivity analysis results are available upon request to the authors via e-mail.

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