The growth stage of Japanese game apps market: A case study and simulation

Makoto Kimura
Nagano University, Faculty of Business and Informatics
Shimonogo 658-1, Ueda City, Nagano Prefecture, 386-1298, Japan
Tel: +81-268-39-0176
E-mail: kimura@nagano.ac.jp, kmakoto@bekkoame.ne.jp

Abstract

This empirical case study examines the marketing in the growth stage of the Japanese game apps market by the classification of business strategies for the game apps such as the lean startup strategy and the imitation strategy. To conduct this examination, a model to calculate the sales performance of game app superstars is proposed using system dynamics techniques, and the transition of key performance indicators is estimated. An examination of the case study and the simulated results of the model suggest that (1) mass media advertisements through game app TV commercials work well for three months, even though five months after an official service release; (2) under game apps that adopted the imitation strategy, the number of multihoming users reaches approximately half of the new registered users and the average revenue per paid user (ARPPU) is higher than that adopted under the lean startup strategy; (3) the game apps adopted the lean startup strategy or imitation strategy coexist in the stage of growth market.

Keywords: multihoming, average revenue per paid user, mobile games, video game industry, system dynamics, Bass model

1. Introduction

After 2011, smartphones, such as the Apple iPhone and Android phone, spread throughout the global market. The mainstream smartphone applications are game apps, which consumers can search for and download through the Apple iTunes App Store or the Google Play Store.

In 1997, the video game market size reached its peak when console game revenues were an estimated 538.9 billion Yen (JPY) in Japan. Subsequently, the market size generally shrank and expanded again in 2006. Annual revenues for console game hardware reached its peak at an estimated 329.1 billion JPY when the Nintendo DS (Japanese version) was released in 2007. Thereafter, annual sales decreased remarkably. In 2004, the online game market grew gently; however, this growth was not large enough to beat the Japanese video game industry. The social network game market targeting feature phone customers expanded quickly in 2010, but peaked in 2011. After 2011, the game apps market targeting smartphone customers grew rapidly and achieved the top share of the Japanese video game market (shown in Figure 1).

Moore (2005) describes the category maturity life cycle model consisted of three stages of market development such as growth market, mature market and declining market. In that sense, the Japanese game apps market has been in the stage of growth market.

Anderson (2009) proposed the "freemium" revenue model, which has the particular trait of 90% free users and 10% premium or paid users. The freemium revenue model fits the game apps business. Game apps are basically free of charge to download and play, and their public indicators of popularity are download ranking and number of downloads through the Apple iTunes App Store or the Google Play Store. Therefore, every smartphone user can easily know the names of the popular game apps and download several game apps and play them. Game apps business players tend to deploy the same game apps for both Apple iOS and Android to achieve rapid business growth.

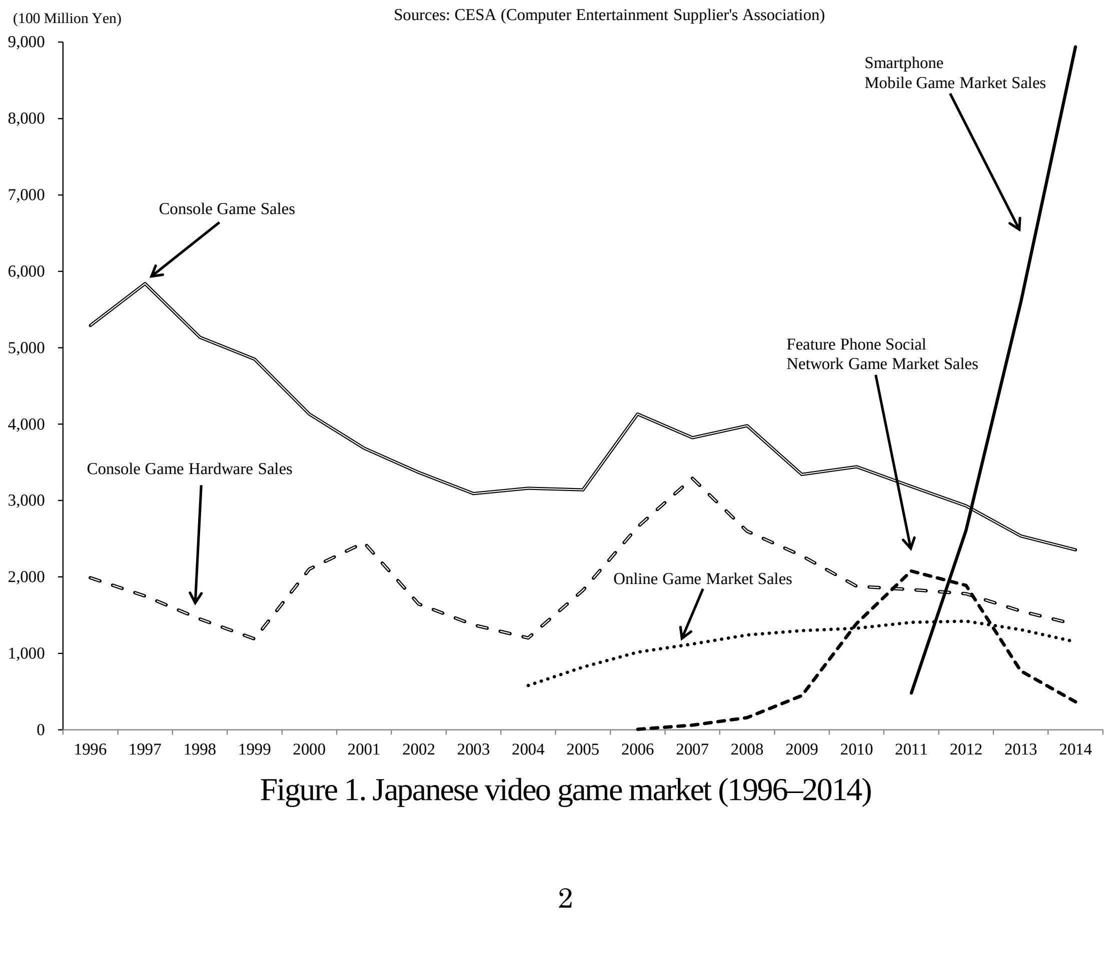

Figure 1. Japanese video game market (1996–2014)

Download frequency, registered users, free users, paid users, and monthly purchase amounts per paid user or average revenue per paid user (ARPPU) are applicable as key performance indicators (KPIs) for the game apps business. These KPIs are generated from transactions for game apps installed in smartphones and on application servers. It is very difficult for third parties or researchers to gain this management information unless it is disclosed.

By the classification of business strategies for the game apps such as the lean startup strategy and the imitation strategy (Table 1), this study develops an argument for the marketing in the growth stage of the Japanese game apps market through an examination of KPI fluctuations in the case study and by engaging in a simulation analysis of the diffusion between game apps. To do this, the top ranked game apps, such as "Puzzle & Dragons" (Puzdra) and "Monster Strikes" (Monst), which recorded 39.5 million downloads in Japan in nearly four years between February 2012 and December 2015, are described. Then, a model to calculate game app sales performance is proposed using system dynamics techniques. The transition of KPIs is then estimated. Finally, through an examination of the case study and the model's simulated results, the new findings and the implications of this study are identified.

In this study, the lean startup strategy is defined as the game apps business player adopting a lean startup methodology (Ries, 2011) and attaining a first-mover advantage. In this strategy, the game apps are developed as a "minimum viable product," distributed free of charge, and updated frequently. Through the version-up process, game apps are improved and made more sophisticated. They are then monetized as an implementation of the freemium revenue model at the appropriate time. This strategy is not unusual for the game app business or e-business of small and medium enterprises.

Table 1. A classification of business strategies for the game apps

	Lean startup strategy	Imitation strategy
Definition	To adopt a lean startup methodology (Ries, 2011) and attaining a first-mover advantage for the game apps business.	To achieve a latecomer advantage as an opposite concept to the lean startup strategy for the game apps business.
Description	To develop the game apps as a "minimum viable product," distributed free of charge, and updated frequently, through the version-up process, game apps are improved and made more sophisticated. To monetize as an implementation of the freemium revenue model at the appropriate time.	To develop the game apps imitating and reinventing the functions of advanced game apps and reinventing for the differentiation.
Risk	The deliverables are so precisely lean artifacts and a business structure that are logical and preferable to customers, that they are likely to be imitated.	An extremely explicit imitation has the risk of being regarded as copyright infringement.
Related Literature	Ries (2011) Blank (2013) Eisenmann, Ries, Dillard (2013)	Schnnars (1994) Shenkar (2010) Staykova and Damsgaard (2015)
Example	Puzzle and Dragons (Puzdra)	Monster Strikes (Monst)

The deliverables of the lean startup strategy, such as a minimum viable product and business model, are precisely lean artifacts and a business structure that are logical and preferable to customers. Thereby, this strategy contains an essential problem likely to be imitated. In this study, the imitation strategy (Schnnars, 1994) to achieve a latecomer advantage is defined as an opposite concept to the lean startup strategy in the game apps business. The differentiation from advanced game apps is very important for the imitation strategy because extremely explicit imitation has the risk of being regarded as copyright infringement. The implementation of an imitation strategy also seems commonplace in e-business (Staykova and Damsgaard, 2015). However, the transition of KPIs between the lean startup strategy and the imitation strategy have not been clarified numerically and argued in the previous research.

2. Literature Review

2.1. Entrepreneurship and management strategy

Ries (2011) proposed the "lean startup" methodology for launching a company on the basis of the Toyota Production System known as lean manufacturing and agile software development. The core element of this methodology is the feedback loop composed of building, measuring, and learning as the growth engine. To begin this cycle, a "minimum viable product" (MVP) is created. After several feedback loops, "pivoting" the product direction and/or customer targeting seem to be very important activities. Blank (2013) defined the startup as "a temporary organization designed to search for a repeatable and scalable business model" and emphasized the importance of styles, such as "to listen to customers" and "quick, responsive development." Eisenmann, Ries, and Dillard (2013) examined the process of hypothesis-driven entrepreneurship and explored the rationale for lean startup practices. Schnnars (1994) examined 28 detailed case histories that indicate that imitators have clear advantages relative to pioneers, and suggested managing imitation strategies. Shenkar (2010) also suggested making imitation a core element in a competitive strategy and proposed three strategic types of imitators, such as the pioneer importer, the fast second, and the come-from-behind.

Since the 2000s, platforms theories have developed. From an economics perspective, the product and the software are regarded as multi-sided platforms representing the existence of the "network effect" that arises between the "two sides" of the market (Rochet and Tirole, 2003; Evans, 2003; Armstrong, 2006). The monopoly platform or competing platforms are economically analyzed by modeling the single homing or the multihoming market (Rochet and Tirole, 2003; Sun and Tse, 2009; Choi, 2010). Landsman and Stremersch (2011) noted the significance of multihoming across platforms (video game consoles) rather than the mere size of the network in the U.S. home video game market.

2.2. Diffusion model and technological substitution model

Research on the new product diffusion model was initiated by Bass (1969). The Bass model assumes that potential adopters (users) are influenced by two means of communication: mass media (external influence) and word-of-mouth (internal influence). Bass (1969) adopted coefficients of external influence and internal influence (Mahajan et al. 1990a, 1990b, 1995).

The Lotka–Volterra competition (LVC) equations (Lotka, 1924; Volterra, 1926) include a set of coupled logistic differential equations to model the interaction of biological species competing for the same resources. Modis (1997) discussed the dynamics of technological competition in the market based on the LVC equations and introduced six types of interactions among technologies: competition, predator–prey, mutualism, commensalism, amensalism, and neutralism. Pistorius and Utterback (1996, 1997) used the modified LVC equations to model the interactions of technologies in three modes—pure competition, symbiosis, and predator–prey—by changing the algebraic signs of the competition coefficients in the two competitor LVC equations. Mordis and Prat (2003) compared the LVC equations and the Bass model using a novel graphical technique and suggested that the LVC equations are not well suited as an analogous model for the Bass model because the Bass model has a nonzero time derivative at zero, whereas the LVC equations do not.

2.3. Massively Multiplayer Online Game (MMOG)

In research on MMOG, Nojima (2007) analyzed the relationship between the pricing models and user motivation for MMOG play. She proposed two types of pricing models, including a monthly fee model and a per-item billing fee model, and calculated the total sales amounts of the MMOG business. The attempts to understand consumer behavior with respect to free online games and accessory selling or per-item billing are also discussed (We et al., 2013; Hanner and Zarnekow, 2015). As another research area, in-game advertising effects in the virtual world, are measured and discussed (Lewis and Porter, 2010; Terlutter and Capella, 2013). However, growth of the sales amount of superstars and the product life cycle seem not to be recognized as academic themes of MMOG research.

On the basis of the previous studies, this paper adopts the lean startup methodology and the imitation strategy for the game apps business. Moreover, the system dynamics (SD) model integrates the Bass model with a pricing model for MMOG and multihoming users.

3. Case study

This study adopts two cases of top ranked game apps to describe the implementation of the lean startup strategy and the imitation strategy in the Japanese game apps market from 2012 to 2015.

3.1. Puzdra case

GungHo Online Entertainment, Inc. (GungHo) began providing the game app, “Puzzle & Dragons” (Puzdra) on February 20, 2012. Puzdra was ranked first in both the Apple iTunes App Store and the Google Play Store for Japanese markets. Puzdra is a game app that combines the key elements of a puzzle game, a dungeon-crawling role playing game (RPG), and a monster collecting game. The puzzle is solved by color matching drops using a single finger stroke. The game player’s monsters can be grown, and levels are increased by repeating the composition though a combination of base monster and material monsters. By combining a monster that grows to the highest level and a monster for evolution, the game player can obtain the evolved monster and, in this way, expand the collection of monsters.

The Puzdra case adopts the freemium model in which basic play is free. However, the game player must use a “mahou seki” (magic stone) to continue when the game is over. In the game, the magic stones are delivered through a campaign and the completion of the dungeon. Moreover, a game player can purchase them in cash in “a shop” in the game [1].

GungHo began to broadcast Puzdra television commercials on October 15, 2012. The story was that “Puz,” the son of a distinguished “Puzzle” family, and “Dra,” the daughter of a caring RPG family, met and had a wedding ceremony. Broadcasting this TV commercial increased the downloading frequency. Subsequently, new Puzdra downloads were more than one million every month. Since June 2014, the “Arashi,” the most famous male idol group in Japan, was appointed as the image character of Puzdra and has appeared on the television commercials. GungHo, a listed company in Japan, discloses game app performance, including monthly download frequency and quarterly sales amounts. Figure 2 shows the version number transition and accumulated download frequency of the Puzdra case.

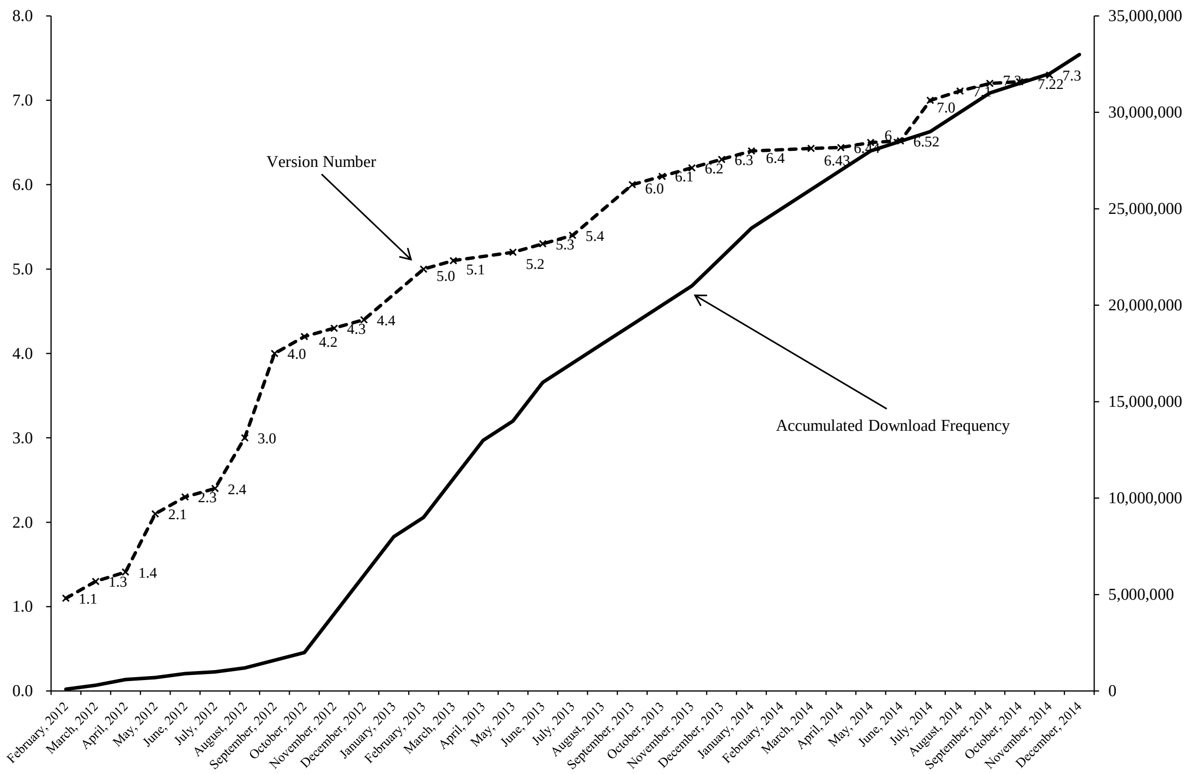

Figure 2. Transition of Puzdra version number (2012–2014)

In the version 1.x–2.x generation, Puzdra improved in quality and fixed bugs and specifications for half a year. Version 4.0 accumulated downloads increased rapidly. This transition of version-up and download frequency seemed to occur from the appearance of the lean startup strategy, which produced the MVP and performed customer development and fragile product development. In the Puzdra case, the direction of the business was also pivoted. For example, in version 5.3, the upper limits of the monthly purchase amounts for young people were set as follows: 5,000 JPY for under 16 years old and 20,000 JPY for under 20 years old. Moreover, the "noryoku kakusei" (ability-emergence) system was released in version 6.0, which strengthened a monster by composing a specific monster (base monster) at the highest level and the "noryoku kakusei" monster, or the same monster.

3.2. The Monst case

"Monster Strike" (Monst) developed by mixi, Inc., the first Japanese social network service (SNS) company, was distributed on October 10, 2013 and became very popular through its "hippari hunting RPG" (pulling and flipping my monster and attacking enemy monsters using reactions from collisions with walls and other monsters). Monst also adopted collaboration play with up to four players, which was a competitive advantage against Puzdra. Catalysts are special items used to evolve monsters. The game player can evolve the largest grown monsters through a combination of catalysts, such as Stoans and Sharls. The "orb" of Monst has the same functions as the magic stone of Puzdra. The pricing system for the orb is the same as that of the magic stone. Since August 13, 2014, the upper limits of the monthly purchase amounts for young people were set as they are in Puzdra.

On March 1, 2014, mixi began to broadcast three types of television commercials for Monst and targeted high school students, female undergraduates, and salaried employees. mixi also emphasized multi-play entertainment with four players and distributed commercials through YouTube.

Moreover, mixi changed the content of the television commercials each quarter and displayed 372 Monst advertisements on main stations and airport places in 2004.

Monst's subsequent game app closely resembles the characters, menu structure, and profit model of the advanced game app, Puzdra [2]. However, the Monst case succeeds in emphasizing differentiation through the multi-play function for a maximum of four game players and collaboration to complete quests. These features indicate that Monst has implemented the imitation strategy.

3.3. Transition of game app performance

An app marketing company, Metapas (2014), reported as follows. Since November 2012, Puzdra has recorded the top sales in the Japanese market (the top rank in the game category) at the Apple iTunes App Store and the Google Play Store. However, in May 2014, Monst won first place and Puzdra ranked second and, subsequently, both repeated their ranking almost every day. In November 2014, Monst recorded the highest monthly daily sales in the Japanese app market. Moreover, Metapas pointed out that only Puzdra and Monst ranked first in the Japanese Apple iTunes App Store and the Google Play Store in 2014.

According to the GungHo financial statement report, the Puzdra sales ratios in the GungHo group were 56.5% in 2012, 91.1% in 2013, 91.5% in 2014, and 88.6% in 2015. Monthly accumulated sales amounts from October 2012 to December 2015 were set assuming quarterly sales to monthly sales distribution ratios of 30%, 30%, and 40%. Finally, accumulated sales performance amounts for Puzdra were estimated as 456,912,706,000 JPY.

The target age population in 2012 was 75,797,000 individuals, comprising men and women aged 10 to 59 years, as obtained from the Statistics Bureau of the Ministry of Internal Affairs and Communications in Japan. GungHo and mixi did not disclose the numbers of monthly free users, monthly paid users, and ARPPU.

Since May 2014, mixi has stopped publishing accumulated download frequency information in the Japanese market and has disclosed these figures only for the global market. Thereby, the accumulated download frequency of Monst in the Japanese market is estimated using linear interpolation from the bar graph drawn in the financial settlement briefing materials. Assuming a 90% sales ratio of Monst in the mixi content department and distribution quarterly sales to monthly sales ratios of 30%, 30%, and 40%, the monthly accumulated sales amounts from October 2013 to December 2015 were set. Finally, the accumulated sales performance of Monst was estimated at 245,927 million JPY. Figure 3 shows the accumulated performance of Puzdra and Monst for 2012–2015.

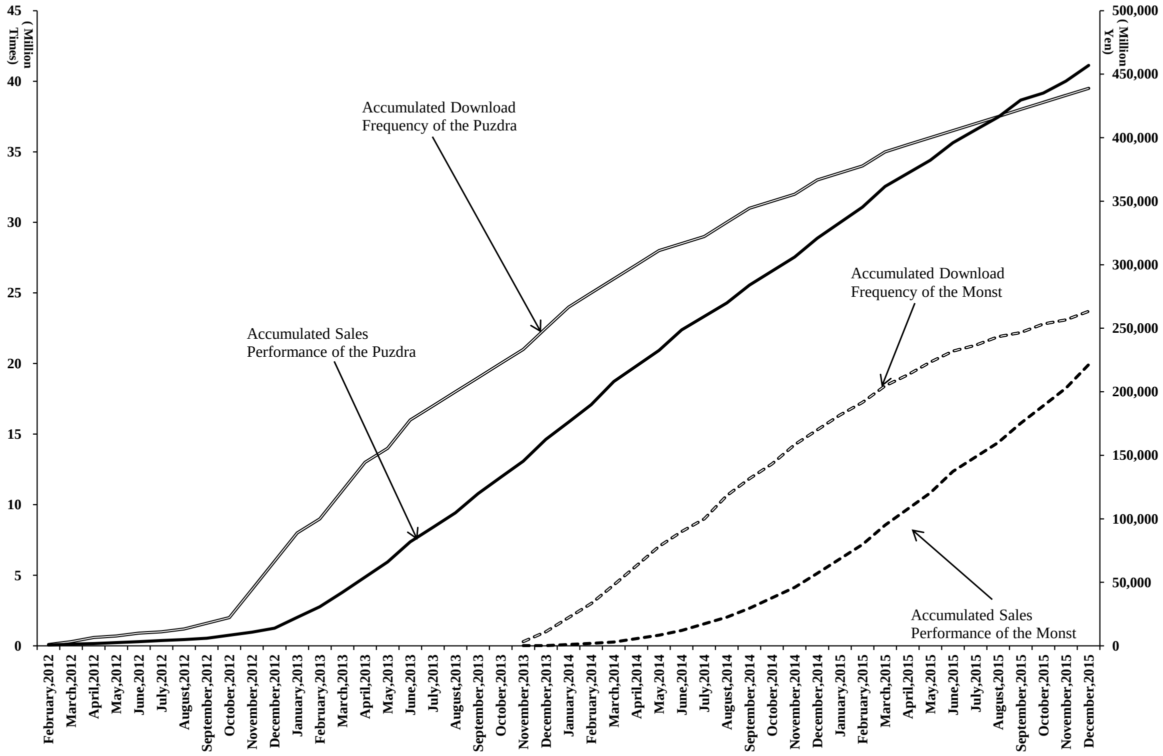

Figure 3. Accumulated performance of Puzdra and Monst (2012–2015)

4. Empirical Method and Model

The empirical model is structured to capture the conditions governing the Japanese game apps market and the KPIs of the game apps business. Furthermore, following Sterman (2000) and Shepherd (2014), we adopt the system dynamics and the MCMC (Markov Chain Monte Carlo) methods. The system dynamics is the causal relationship and feedback loop modeling techniques utilizing four types of components to understand the interdependency of complex systems: stock, flow, variable, and arrow [3]. Our model captures the KPIs relevant to the game apps business in Japan (Nojima, 2007), notably the number of registered users, free users, and paid users, monthly download frequency, and monthly sales amounts. In this model, the state of the customer changes dynamically, such as potential user, registered user, free user and paid user. In other words, this modeling of state transition is an application of aging chains (Sterman, 2000, p.470). The number of registered users is calculated using the Bass model. The numbers of free users and paid users are status variables, multiplied by transition rates such as the monthly active user (MAU) rate, rate of charge, and exit rates of free users and paid users. Monthly sales performance is multiplied by the number of paid users and monthly purchase amounts. The number of monthly downloads is assumed to be the same as the number of new registered users.

In the Japanese game apps market, broadcasting of Puzdra TV commercials since October 2012 seems to have dramatically changed the rate of awareness and proficiency of television audiences and formed the base for the diffusion. Therefore, the Monst case, which started in October 2013, is unlikely to represent a gradual word-of-mouth effect. The advertising effect supposedly acted on Monst rather than on Puzdra. Moreover, game users who are familiar with game apps through Puzdra may also have been interested in Monst and played the game. Given this reasoning, the model assumes that the advertising effect for the game app business users and the multihoming effect for free and paid users of Puzdra cause fluctuations in new registered users for Monst. However, in the model, Monst users do not become new registered users of

Puzdra.

As initial conditions, the target age population is set at 75,797,000, which corresponds to the total 2012 population for the 10 to 59 age group from the Statistics Bureau of the Ministry of Internal Affairs and Communications in Japan. The Monst service start period is set as November 2013 (twenty-first months).

The other initial and boundary conditions, except for monthly active user (MAU) rates, and the other constants are set through calibration using the MCMC method [4]. Furthermore, the upper limit for the rate of charge is set at 30%, and the upper limit for the exit rate is set at 40%. Assuming that each user downloads the game app, the integral equations are as follows, where the value for Δt is one month:

game app business potential users = INTEG (–new registered users M–new registered users P, population of target ages*rate of potential diffusion)
Puzdra accumulated download frequency = INTEG (number of monthly downloads P, 0)
Puzdra registered users = INTEG (new registered users P–new actual users P, 50000)
Puzdra free users = INTEG (new actual users P–free escapees P–new paid users P, 50000)
Puzdra paid users = INTEG (new paid users P–paid escapees P, 0)
Puzdra accumulated sales performance = INTEG (monthly sales performance P, 0)
Monst accumulated download frequency = INTEG (number of monthly downloading M, 0)
Monst registered users = INTEG (new registered users M–new actual users M, 0)
Monst free users = INTEG (new actual users M–new paid users M–free escapees M, 0)
Monst paid users = INTEG (new paid users M–paid escapees M, 0)
Monst accumulated sales performance = INTEG (monthly sales performance M, 0)

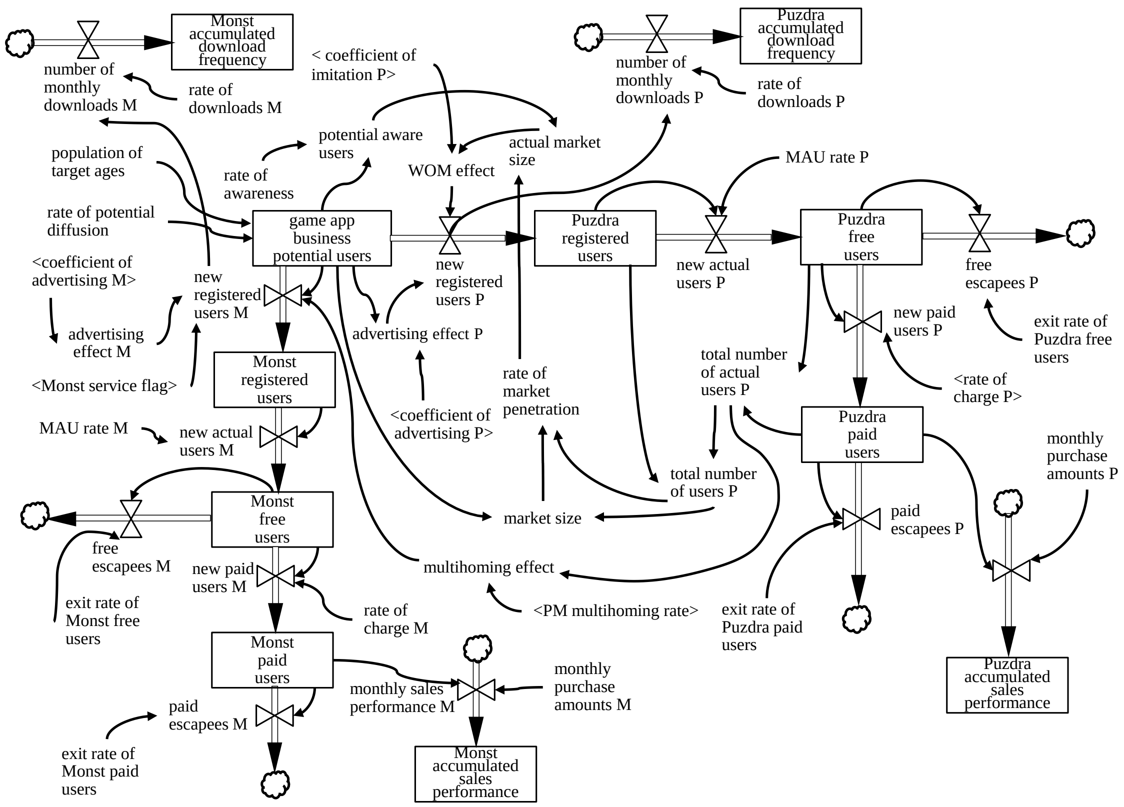

Figure 4. System dynamics diagram of the model

The System dynamics diagram of the model is shown in Figure 4. Assuming that each user downloads the game app means that the rate of downloads P and rate of downloads M are set at 100%. The formulae of the variables in each time are as follows:
advertising effect P = coefficient of advertising P × game app business potential users
potential aware users = game app business potential users × rate of awareness
market size = game app business potential users + total number of users P
rate of market penetration = total number of users P/market size
actual market size = potential aware users × rate of market penetration
WOM effect = coefficient of imitation P × actual market size
new registered users P = WOM effect + advertising effect P
number of monthly downloads P = new registered users P × rate of downloads P
new actual users P = Puzdra registered users × MAU rate P
free escapees P = Puzdra free users × exit rate of Puzdra free users
new paid users P = Puzdra free users × rate of charge P
paid escapees P = Puzdra paid users × exit rate of Puzdra paid users
total number of actual users P = Puzdra free users + Puzdra paid users
total number of users P = Puzdra registered users + total number of actual users P
monthly sales performance P = monthly purchase amounts P × Puzdra paid users
coefficient of advertising M = DELAY FIXED (coefficient of advertising, Monst service start, 0)
advertising effect M = game app business potential users × advertising coefficient M
PM multihoming rate = DELAY FIXED (coefficient of multihoming, Monst service start, 0)
multihoming effect = PM multihoming rate × total number of actual users P
Monst service flag = IF THEN ELSE (PULSE (Monst service start, FINAL TIME), 1, 0)
new registered users M = (advertising effect M + multihoming effect) × Monst service flag
number of monthly downloads M = new registered users M × rate of downloads M
new actual users M = Monst registered users × MAU rate M
free escapees M = Monst free users × exit rate of Monst free users
new paid users M = Monst free users × rate of charge M
monthly sales performance M = monthly purchase amounts M × Monst paid users

The coefficient of imitation and coefficient of advertising, rate of charge, and coefficient of multihoming are not set as constants but as step functions to obtain better fitness with the time-series data (see Appendix). For example, the coefficient of advertising for Puzdra is formulated as follows:
coefficient of advertising P = IF THEN ELSE(PULSE(0,"1st Time"),"1st Value", IF THEN ELSE(PULSE("1st Time","2nd Time"),"2nd Value", IF THEN ELSE (PULSE ("2nd Time","3rd Time"),"3rd Value", IF THEN ELSE(PULSE("3rd Time", "4th Time"), "4th Value", IF THEN ELSE(PULSE("4th Time", "5th Time"), "5th Value", IF THEN ELSE(PULSE("5th Time", "6th Time"), "6th Value", "7th Value"))))))

For the simulation using the empirical model, the three types of management scenarios set each MAU rate as 40%, 60%, and 80%, and were examined through a comparison of the results of the management scenarios. The value of the MAU rate for the most popular mobile app, such as Puzdra or Monst, is regarded as approximately more than 40%. The name of the management scenario, such as the 40-40 scenario, stands for the condition that each MAU rate of Puzdra and Monst is set as 40%. The coefficients used for the management scenario are shown in Table 1 of Appendix.

5. Results

By performing numerical integration from February 2012 to December 2015, the simulated results of the model are shown in Table 2.

Table 2. Simulated results of empirical model

	40-40 scenario	60-60 scenario	80-80 scenario
payoff value of parameter estimation	-0.0023	-0.0025	-0.0024
rate of potential diffusion	85%	85%	85%
rate of awareness	17.89%	13.94%	10.72%
game app business potential users	64,427,452	64,427,452	64,427,452
MAPE of Puzdra accumulated sales performance	16.11%	16.14%	15.19%
MSE of Puzdra accumulated sales performance into bias (U^m)	0.083	0.024	0.0346
MSE of Puzdra accumulated sales performance into unequal variances (U^s)	0.033	0.1244	0.0647
MSE of Puzdra accumulated sales performance into unequal covariation (U^c)	0.8838	0.8516	0.9007
MAPE of Puzdra accumulated download frequency	12.85%	13.8%	19.26%
MSE of Puzdra accumulated download frequency into bias (U^m)	0.0111	0.0304	0.0268
MSE of Puzdra accumulated download frequency into unequal variances (U^s)	0.0794	0.079	0.1356
MSE of Puzdra accumulated download frequency into unequal covariation (U^c)	0.9095	0.8906	0.8376
Puzdra accumulated sales performance (JPY)	457,997,811,712	458,983,899,136	459,565,793,280
Puzdra accumulated download frequency	38,046,088	38,036,116	38,050,368
monthly purchase amounts P (JPY)	5,296.6	3,491.26	2905.63
exit rate of Puzdra free users	4.99%	5.51%	5.58%
exit rate of Puzdra paid users	17.1%	9.85%	8.98%
contribution of advertising effect to the total number of Puzdra registered users	61.21%	54.42%	62.02%
contribution of word-of-mouth effect to the total number of Puzdra registered users	38.79%	45.58%	37.98%
MAPE of Monst accumulated sales performance	13.99%	12.18%	11.85%
MSE of Monst accumulated sales performance into bias (U^m)	0.0832	0.0841	0.0438
MSE of Monst accumulated sales performance into unequal variances (U^s)	0.033	0.0272	0.0817
MSE of Monst accumulated sales performance into unequal covariation (U^c)	0.8838	0.8887	0.8745
MAPE of Monst accumulated download frequency	2.73%	0.35%	2.15%
MSE of Monst accumulated download frequency into bias (U^m)	0.0155	0.0314	0.0198
MSE of Monst accumulated download frequency into unequal variances (U^s)	0.1399	0.1778	0.1291
MSE of Monst accumulated download frequency into unequal covariation (U^c)	0.8446	0.7908	0.8511
Monst accumulated sales performance (JPY)	215,604,805,632	216,723,570,688	217,599,311,872
Monst accumulated download frequency	23,516,890	23,498,646	23,522,644
monthly purchase amounts M (JPY)	5,760.11	9,446.11	39,993.4
rate of charge M	15.95%	8.35%	1.65%

exit rate of Monst free users	1%	40%	40%
exit rate of Monst paid users	40%	10.69%	10.13%
contribution of advertising effect to the total number of Monst registered users	20.59%	54.42%	54.02%
contribution of multihoming effect to the total number of Monst registered users	79.41%	45.58%	45.98%

The payoff value of the parameter estimation shows that all scenarios could be better validated. In these scenarios, the validity of the simulated results are confirmed by the mean absolute percent error (MAPE) of the data, such as accumulated download frequency and accumulated sales performance [5]. The MAPE values of accumulated download frequency are approximately 1 to 19%, and those for accumulated sales performance are 12 to 16%, which are evaluated as reasonably good. Moreover, the Theil inequality statistics indicate that the error is concentrated in an unequal covariation, which means that the model effectively captures the mean and the trends in the data. In other word, the error is unsystematic (Sterman, 2000).

The graphs of the simulated results for the 60-60 scenario are shown in Figure 5. The graphs for sales performance and download frequency from the other scenarios seem to be the same as those of the 60-60 scenario. However, in the 80-80 scenario, the monthly purchase amount M (ARPPU of Monst) from the optimization is 39,993.4 JPY, which is higher than the monthly upper limit amount for the under-aged group, at 20,000 JPY. For this reason, 80-80 scenario is not appropriate to the Japanese game apps market. In the 40-40 scenario, the exit rate of Monst free users is only 1%. For these reasons, the 60-60 scenario seems to be plausible scenario. The transition of the KPIs and the monthly sales performance for the 40-40 and 60-60 scenarios are shown in Figure 6 and Figure 7. The empirical simulation produces the following seven key results.

I. The number of potential users for the game apps business of more than 64 million people—equivalent to approximately 85% of the productive population in Japan—is anticipated.
II. Although more than five months have passed since the service start of the game app, the advertising effects of the TV commercials can work well on potential users.
III. The number of Puzdra free users is always higher than that of Monst.
IV. The monthly purchase amount M (ARPPU of Monst) and the exit rate of Monst paid users are higher than those for Puzdra.
V. The contribution of advertising effect to the total number of Puzdra registered users is more than 50%, indicating that the advertising effect is stronger than the word-of-mouth effect.
VI. Approximately half the number of new registered users of Monst are multihoming users.
VII. Monst monthly sales amounts exceed Puzdra monthly sales amounts from January 2015.

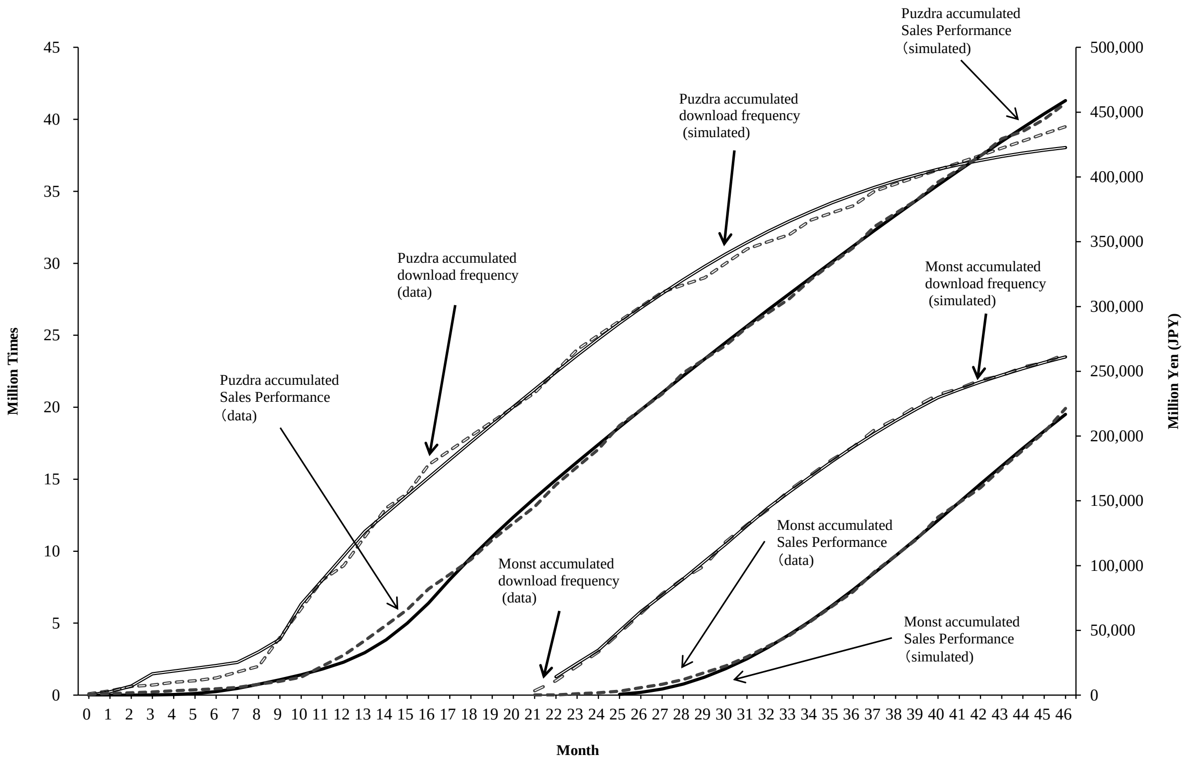

Figure 5. Results of the 60-60 scenario

Result I indicates the initial condition of potential users of the game apps as the target age population (75,797,000) multiplied by the rate of potential diffusion (85%). Figure 7 shows the transition of the advertising effect of Puzdra, which indicates result II. Figure 6 shows result III. The advertising effect of Puzdra is highest in four months, from the ninth to the twelfth month (November 2012 to February 2013), corresponding to the TV commercial broadcast launch period. Table 2 shows results IV, V, and VI.

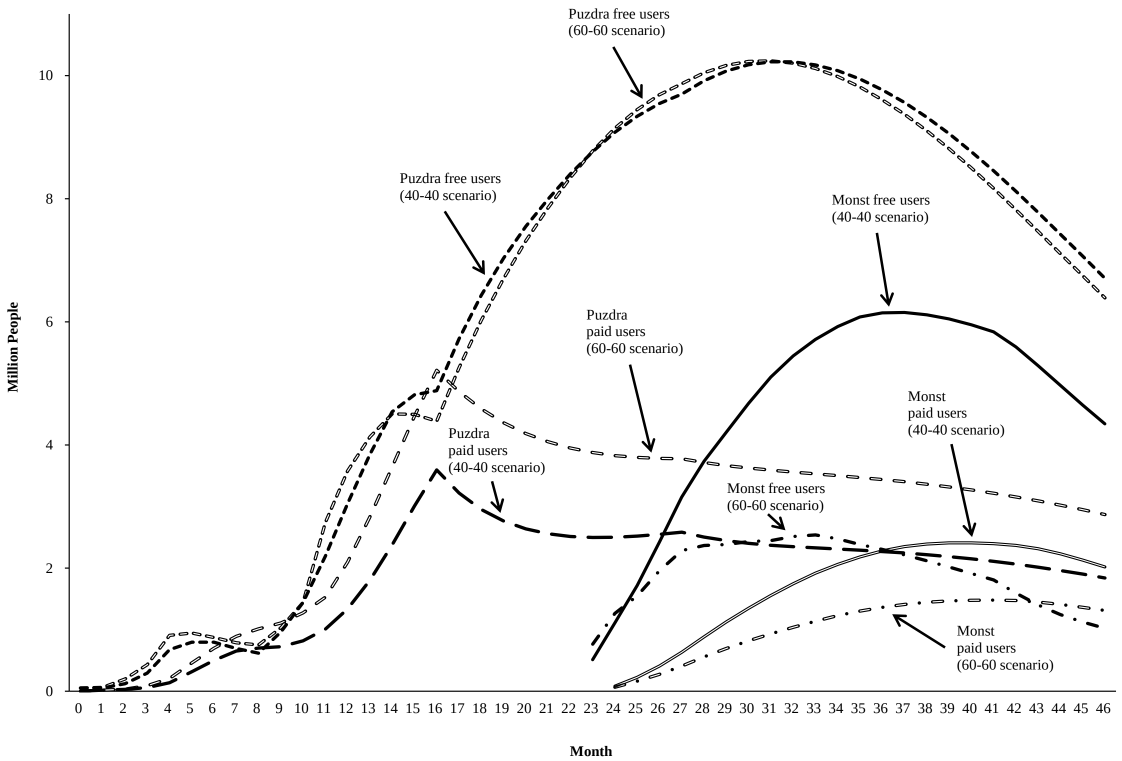

Figure 6. KPI transition of 40-40 scenario and 60-60 scenario

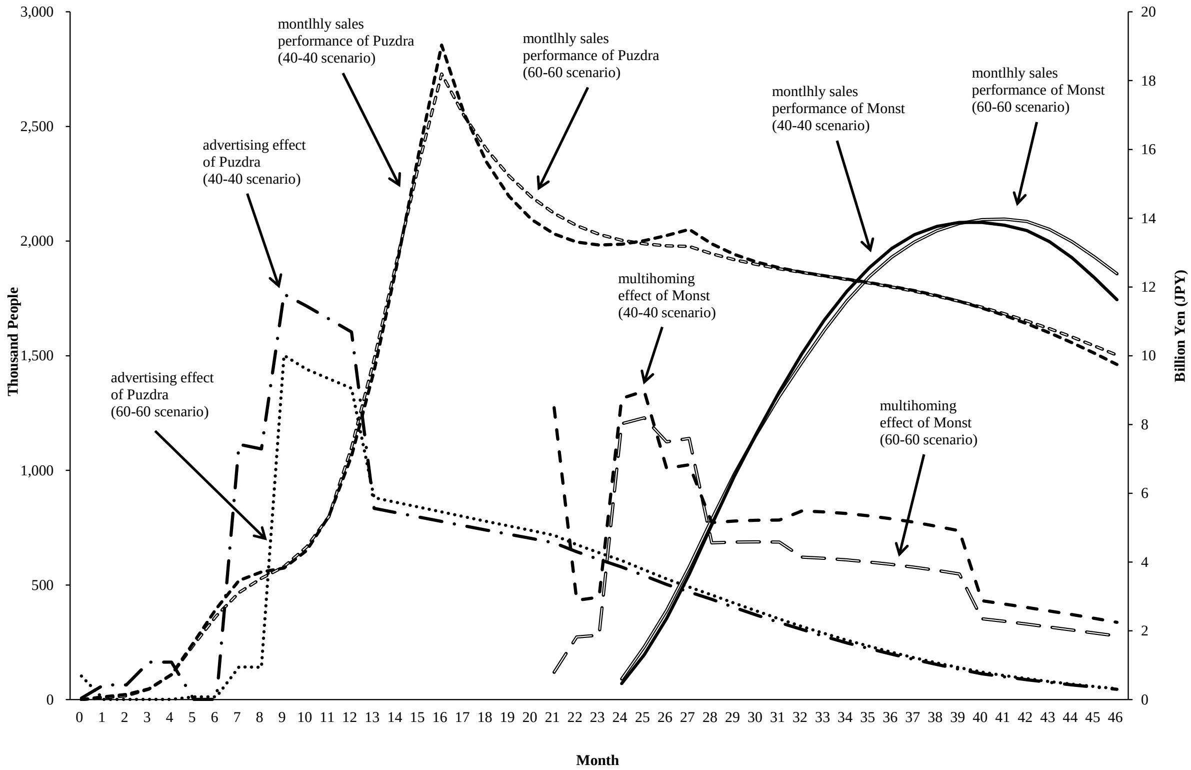

Figure 7. Each effect and monthly sales performance of 40-40 scenario and 60-60 scenario

As Figure 7 shows, in the 40-40 scenario and the 60-60 scenario, the multihoming effect of Monst is the highest in the four months from the twenty-fourth to the twenty-seventh months (February to May 2014), corresponding to the TV commercial broadcast launch period.

Subsequently, the multihoming effect reached the plateau stage from the twenty-eighth to the thirty-first month (June to September 2014), corresponding to the third series of the TV commercial broadcast launch period. In the end, result VII is obtained by the cross point between the trajectories of the monthly sales performances of Puzdra and Monst in Figure 7.

6. Discussion

In the Monst case, mixi stated that download frequency is counted only once for every user. However, in the Puzdra case, GungHo does not make statements similar to those of mixi, indicating that download frequency might be counted multiple times for a user. In that case, reducing the number of potential game apps users by half may be appropriate. Generally, in the game apps business, heavy users who positively obtained the published information before the service started are not the majority. In contrast, light users who downloaded and played the app by learning its name through TV commercials seemed to account for most users.

Comparing Puzdra and Monst, the exit rate of Puzdra is comparatively low and high customer loyalty is expected. Meanwhile, the exit rate of Monst paid users is comparatively high, implying that customer loyalty is low, but ARRPU of Monst is higher for Puzdra. In addition, even though the multihoming ratio per month is approximately 10% for Puzdra, multihoming users play an important role for Monst.

An examination of Puzdra and Monst, and the simulated results of the model that calculates the KPI transition, reveals the new findings of this study. These findings are as follows. The game apps business adopted a lean startup strategy and an imitation strategy, which earned the same level of profits during the same period. However, the game app business that adopted an imitation strategy may earn higher revenues and win the come-from-behind ranking victory in the market.

The marketing activities of the lean startup strategy for the game apps as seen in the Puzdra case are described as follows. Word-of-mouth activities and advertising activities, especially TV commercials, are equally effective in increasing the number of new users. Regarding technical development activities to maintain the low exit rate for game app users, high frequent version-ups, including bug fixes, functional improvements and enhancements, and periodic event provisions, are implemented.

The marketing activities of the imitation strategy for the game apps to be seen in the Monst case are described as follows. Advertising activities, especially TV commercials, are also effective in increasing the number of new users. Regarding the technical development activities to appeal to advanced game apps users, advanced features including graphic characters, the user interface items, and pricing mechanisms, are imitated. Moreover, a differentiated primary function is also implemented. Through advertising, imitation, and differentiation activities, an increase in multihoming users is expected. However, the exit rate of free users and/or paid users would be higher for game apps that adopt the lean startup strategy.

The lean startup strategy fits well for the game apps, and providing imitated game apps is not uncommon. The increase in multihoming users through the diffusion of the imitated game apps does not adversely affect advanced game apps. In contrast, the number of multihoming users can reach approximately half of the new imitated game app users. Such dynamic stability from game app diversity and market growth is suggested.

The lean startup strategy would link the high consumer loyalty not to the high ARPPU but to the number of free users. This indicates that the game apps that adopted the lean startup strategy should keep or increase the number of free users to countervail against the imitation strategy. In contrast, the imitation strategy would aim at higher ARRPU and the increase of the number of paid users to improve the profitability of game apps, even though the customer loyalty is low.

Moreover, this study clarifies the importance of mass media advertising in a startup strategy and an imitation strategy for the game apps business. The simulated results indicate that the advertising effect from TV commercials works well in three months, even though five months after the service is released—and later—this effect decreases suddenly. Therefore, once the TV commercial is adopted, new ones must continue to be broadcast to increase revenue. This phenomenon has a significant influence on the game apps business. In other words, the imitation strategy for the game apps business may need to realize the customer development (advertisement) financing that can maintain TV commercials' nationwide broadcasting to exceed the monthly sales performance of the lean startup strategy.

7. Conclusion

This study used system dynamics techniques and approaches outlined in previous studies to simulate the diffusion of game apps in Japanese market, and attempted to develop the argument of business strategies and marketing for the game apps in the stage of growth market such as the lean startup strategy and the imitation strategy.

The major findings are as follows. First, mass media advertising is very important for game apps businesses that adopted the lean startup strategy and the imitation strategy. The simulated results indicate that the advertising effect from TV commercials works well for three months, and even five months after the official service release. Second, the number of multihoming users can reach approximately half of new registered users of game apps that adopted the imitation strategy. Third, the lean startup strategy can keep or increase the number of free users to countervail against the imitation strategy. In contrast, the imitation strategy will aim at higher ARRPU and the increase of the number of paid users. Forth, the competition among game apps between the lean startup strategy and the imitation strategy suggests the dynamic stability in the stage of growth market of Japanese game apps market.

This study has its limitations. Top ranked game apps, Puzdra and Monst may not be typical cases for the game apps business; therefore, the argument for the lean startup strategy and the imitation strategy through an examination of their cases and the simulated results of the model would too greatly exaggerate the special conditions. To supplement the tests, some field surveys and simulations are required. The model in this study can only be used to examine the transition of KPIs of a few game apps during the stages of growth market. Moreover, an examination of the competition among several game apps, a modified model, integration of other effects into advertising, word-of-mouth and multihoming effects should be developed in future studies.

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Notes

[1] The magic stone functions are as follows: to pull a lottery to get a strong monster with five stones to recover stamina using a stone and continue to play when the game is over using a stone. The pricing system is as follows: 100 JPY for a stone, 500 JPY for six stones, 900 JPY for twelve stones, 3,800 JPY for sixty stones, and 5,000 JPY for eighty-five stones.
[2] When playing Monst, the user can select and obtain a partner monster among Red Smydra,

Blue Smydra, and Green Smydra, which closely resemble Tyrra, Plessie, and Brachy, the partner monsters of Puzdra.

[3] The system dynamics model has the advantage of generating and executing time-differential equations by modeling the compound domain that the mathematical model does not establish and can graphically combine several types of concepts (Sterman, 2000). The system dynamics approach is well suited to problem structures, such that the Bass diffusion model has been applied to the adoption of new technologies in other areas and gives the modeler the opportunity to investigate general dynamic tendencies to understand and explore the nature of the problem (Shepherd, 2014).

[4] The Markov Chain Monte Carlo (MCMC) method is calculated using Vensim Professional 6.3G software (Ventana Systems, 2016) through calibration by comparing time-series data, such as accumulated download frequency and accumulated sales.

[5] For typical business data, the case of less than 10% of the value of MAPE represents highly accurate forecasting, and the case of less than 20% is good forecasting or, in the other words, practical (Lewis 1982).

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Appendix. Table 1. List of coefficients used for the management scenarios

		40-40 scenario	60-60 scenario	80-80 scenario
coefficient of advertising P	1st Time	1	1	1
	2nd Time	2	2	2
	3rd Time	3	3	3
	4th Time	4	4	4
	5th Time	5	5	5
	6th Time	8	8	8
	1st Value	0.0001	0.0016	0.0171
	2nd Value	0.001	1e-005	1e-005
	3rd Value	0.0026	1e-005	0.0029
	4th Value	1e-005	0.0002	0.004
	5th Value	0.0178	0.0023	0.0171
	6th Value	0.0293	0.0248	0.0276
	7th Value	0.0158	0.0166	0.015
coefficient of imitation P	1st TimeB	1	1	1
	2nd TimeB	2	2	2
	3rd TimeB	3	3	3
	4th TimeB	4	4	4
	5th TimeB	6	6	6
	6th TimeB	14	14	14
	1st ValueB	9.9999	10	1e-005
	2nd ValueB	6.8165	9.9999	0.6996
	3rd ValueB	0.0001	8.4238	0.0001
	4th ValueB	0.0786	0.8418	1e-005
	5th ValueB	1e-005	2.1119	0.0068
	6th ValueB	0.2467	0.3208	0.4515
	7th ValueB	0.2773	0.3325	0.4372
rate of charge P	1st TimeA	1	1	1
	2nd TimeA	2	2	2
	3rd TimeA	5	5	5
	4th TimeA	11	11	11
	5th TimeA	16	16	16
	6th TimeA	30	30	30
	1st ValueA	0.3	0.3	0.3
	2nd ValueA	0.3	0.3	0.3
	3rd ValueA	0.3	0.3	0.3
	4th ValueA	0.2286	0.2633	0.2336
	5th ValueA	0.0492	0.0379	0.0171
	6th ValueA	0.0373	0.0315	0.0162
	7th ValueA	0.01	0.01	0.01
coefficient of multihoming	1st TimeC	1	1	1
	2nd TimeC	2	2	2
	3rd TimeC	3	3	3
	4th TimeC	4	4	4
	5th TimeC	7	7	7
	6th TimeC	12	12	12
	1st ValueC	0.1207	0.01	0.0416
	2nd ValueC	0.0397	0.0222	0.013
	3rd ValueC	0.1135	0.0928	0.0131
	4th ValueC	0.0834	0.0835	0.0234
	5th ValueC	0.0622	0.0497	0.0404
	6th ValueC	0.0655	0.0452	0.0325
	7th ValueC	0.0395	0.03	
coefficient of advertising M	1st TimeD	1	1	1
	2nd TimeD	2	2	2
	3rd TimeD	3	3	3
	4th TimeD	4	4	4
	5th TimeD	5	5	5
	6th TimeD	8	8	8
	1st ValueD	1e-005	0.0267	0.0142
	2nd ValueD	0.0129	0.0164	0.0195
	3rd ValueD	1e-005	0.0035	0.032
	4th ValueD	0.0022	0.0001	0.0256
	5th ValueD	0.0192	0.0197	0.0192
	6th ValueD	0.0177	0.0257	0.0286
	7th ValueD	0.0123	0.0282	0.0337