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행위자 기반 시뮬레이션을 이용한 확률형 아이템 시장에서 확률 조작의 영향 분석

Agent-Based Simulation of the Effect of Probability Manipulations on Loot Box Markets

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Abstract

Loot boxes, which are in-game products, comprise various random in-game items. They have become the main source of revenue for the video games industry. There are debates on the effects of probability manipulation by providers and the policy implications thereof. Previous research attempted to analyze this issue; however there were some limitations: a long-term perspective does not fit the video game market as it has a short product life cycle, and information diffusion on social networks was ignored. In this study, additional revenues of producers are estimated by fixing the odds of loot boxes and analyzing the effects of the information generation process using agent-based simulations. The agent-based model consists of a monopolist loot box provider and a plurality of consumers, who are connected through a social network. The results suggest a method for estimating the short-term profit gained by a loot box producer from probability distortions and show that the collective inspection of consumers detects the manipulation faster. These results will help regulators design better loot box regulation policies.

Keywords: Loot box, Agent-based simulation, Information Diffusion

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1. Introduction

Loot boxes, which are virtual gaming products, provide random, virtual in-game items. They have become the cause of controversy and discussion in the gaming industry. Loot boxes have become one of the main sources of revenue in the gaming industry, (Nakamura, 2018, Taylor, 2018) and the industry has grown drastically, since adapting the "free to play" model, whereby games are provided for free but virtual items are sold for use in games. One of the issues being discussed is the transparency of the probability distribution for rewards and the distortions thereof. In this study, the effects of the distortions of the probabilities of loot boxes on the short-term revenue of game providers is investigated, and how the information on the probability of loot boxes affects the revenue, is discussed.

1.1 Overview of loot box

1.1.1 Definition of loot box

Various definitions of loot boxes have been suggested by various researchers and regulation authorities. (Nielsen and Grabarczyk, 2018; Jo and Ryu, 2019; Park and Lee, 2018; Koeder, Tanaka, and Mitomo, 2018) However, common elements are used for classifying loot boxes: conditions

necessary for acquirement, level of uncertainty, and utility of reward. Various definitions of loot boxes are in agreement that it a loot box should be acquired upon satisfaction of certain requirements, which is usually paying real/virtual currency or achieving an in-game task, and not for free. They also agree that the reward of the box should be unknown to the game user, and should be determined randomly, hardly reflecting a skill or the effort of the user. Furthermore, the reward of a loot box should be useful in gaming; however, it can have little value in the real world.

1.1.2 Terminology of loot box

In addition to its definition, the terminology referring to the loot box also varies by country, platform, field, and researcher. Its common name is loot box; however, variations in the name, such as "loot crate", "loot case", "loot chest" (Li, Mills, and Nower, 2019) exist. The term originated from "looting", given that the in-game items are acquired after accomplishing a certain goal (e.g. defeating an enemy). (Nielsen & Grabarczyk, 2019) "Gacha", or "Gacha-pon", the Japanese expression of a loot box, is usually used interchangeably with the term "loot box," especially in East Asia. The term originally referred to a Japanese capsule toy vending machine, which contains various toys surrounding a character or theme and mimics the sound of the machine. (Koeder, Tanaka, and Mitomo, 2018; Park and Lee,

2018) Besides, Koeder, Tanaka, and Mitomo (2018) suggested segregating Gacha from the loot box, by focusing on the differences in origin and metaphor – Gacha from a vending machine, and loot box from collectible cards or treasure boxes. Furthermore, there are differences in their roles in business models – Gacha is a key revenue source of "free to play" games, and the loot box is an additional revenue source of paid game titles. In the case of South Korea, an official term and an informal term exist: "확률형 아이템 (Hwak-ryul-hyeong item, stochastic item)" and "랜덤박스(random box)". The official term describes one of its features: uncertainty of the content. The term is used by lawmakers (Bill 1914215, 2015; Bill 2000640, 2016; Bill 2002887, 2016), researchers (Jo and Ryu, 2019; Park and Lee, 2018; Hwang and Shin, 2014; Choi, 2018), and industry (Self-regulation guidelines for developing sound game culture, 2017; Probability of Loot box, 2020). "Random box", the common use term, also describes the uncertainty regarding the content of the loot box; the word originates from a Korean term for a similar marketing strategy, whereby veiled items are sold following a certain theme. The term is widely used by game users, but is not official. (Random Box, 2020) Only Jo and Ryu (2019) used this term in their study, along with the term "stochastic item" to describe this specific type of loot box. The Korean press uses both terms. (Seo, 2016; Seo, 2017)

1.1.3 History of loot box

There are various origins that could be predecessors of the contemporary loot box, and loot boxes inherited several components of various predecessors. The concept of "looting" in-game items or acquiring them from treasure boxes was adopted in early video games, especially in roleplaying games. (Nielsen and Grabarczyk, 2018; Koeder, Tanaka, and Mitomo, 2018), Nielsen and Grabarczyk (2018) pointed out that mechanisms that give reward uncertainty during special events are widely found in various analog games, such as collection card games or chance cards in Monopoly. However, they are not considered as direct ancestors of loot boxes, as they were not designed as marketing strategies. In the case of using uncertainty as a marketing strategy, researchers agree that this concept dates back to collectible picture cards from the 19th century, which were sold with cigarettes or sweets. (Nielsen and Grabarczyk, 2018; Koeder, Tanaka, and Mitomo, 2018) This strategy is used in various areas: Gachapon toy dispensers in Japan, sweets, including small toys like Kinder Eggs, or collectible cards, such as baseball cards or collectible card games. (Nielsen and Grabarczyk, 2018) These predecessors have affected the modern loot box in terms of specific merchandising methods: stimulation of the completion of a card set through an expected number of buys to collect full sets increases with $\Theta(n\log(n))$ (Motwani and Raghavan, 1995),

and classifying the cards by odds. (Nielsen and Grabarczyk, 2018). The direct predecessors of contemporary loot boxes, which introduced a random mechanism as a business strategy and adapted the concept and metaphor, are ZT Online, and Team Fortress 2. (Nielsen and Grabarczyk, 2018; Koeder, Tanaka, and Mitomo, 2018) In the case of East Asia's Gacha system, it originates from capsule toy vending machines, as explained above. The first video game that imported the Gacha system is considered to be MapleStory in 2004, which mimicked a Gacha dispenser. (Jo and Ryu, 2019; Park and Lee, 2018; Kim, 2016; Lim, 2017) The Gacha system has been propagated by attaching it to the collectible card game genre. Kaku-San-Sei Million Arthur was a milestone in the popularization of the Gacha system. It was a huge success as it adapted the Gacha system as the main source of revenue, and characterized each card-reward of Gacha with alluring illustrations. (Park and Lee, 2018; Lim, 2017; Ahn, 2013) Since then, the Gacha system has spread widely, especially in the mobile game market.

1.1.4 Taxonomy of loot boxes

There are various taxonomies to classify various types of loot boxes. Nielsen and Grabarczyk (2018) classified loot boxes by the relation of resources and reward to the real world. An "embedded" type is a resource

or reward that has cash value, and “isolated” is one that does not have cash value. Several studies have classified loot boxes according to their system. Usually loot boxes are sorted into acquisition and strengthening loot boxes; the former provides in-game items, while the latter upgrades existing in-game items to more valuable ones. (Park and Lee, 2018) Hwang and Shin (2014) compartmented loot boxes into box types that provide virtual items independently, a key type that acquires “boxes” while playing games and sells “keys” to release a “box” and acquire the virtual item, and an enhancement type that makes virtual items more useful. Koeder, Tanaka, and Mitomo (2018) found 10 types of Gacha in the literature. Kompu Gacha, which provides rare items by acquiring a given combination of items; Box Gacha grants a set of items with given probabilities; Sugoroku Gacha, which acts as a dice in a board game to unlock special items; Redraw Gacha, which allows for another chance to draw; Open/Closed Gacha distinguished by whether it shows a certain item’s probability to earn; and discounted Gacha, which decreases the price of loot box during specific campaigns.

1.1.5 Regulation

Due to ethical and social controversies surrounding the loot box, governments are going to regulate loot box policies. The Entertainment Software Rating Board (ESRB), a self-regulatory organization for video

games in North America, declared a loot box as not constituting real gambling, but as being a simulation of gambling due to betting with virtual money. (Seo, 2017) Apple forced all "apps offering loot boxes" in its Appstore to "disclose the odds of receiving each type of item to customers prior to purchase." (App Store Review Guidelines, 2018) The Belgian Gaming Commission declared loot boxes as gambling and being illegal, such as FIFA 18, Overwatch, etc. (Yin-Poole, 2018). The Japanese Consumer Affairs Agency declared the marketing of Japanese mobile social games' loot box items as illegal. (Baek, 2012) China introduced regulations enforcing daily limits of purchase, ensuring a quota of items in proportion to consumed amount of loot boxes. (Ye, 2019)

The history of loot box regulation policy in South Korea was described by Park and Lee (2018). It started in the late 2000s, after NEXON introduced the Gacha system to the Korean MapleStory service in 2005. In 2008, K-IDEA (Korea Internet & Digital Entertainment Association) published "Self-regulation code for 'Capsule-like paid item' service," which suggests providing items that have similar value to its price, and does not use the term "gambling." However, this was not followed by producers. In 2011, the Game Rating and Administration Committee began research on loot box markets, including meetings with and investigations of major video game publishers. However, it did not produce satisfactory

results, as providers denied contributing to information on loot boxes. After the loot box issue was raised internationally, K-IDEA declared the enforcement of self-regulation in 2014. K-GAMES (Korea Association of Game Industry), a successor of K-IDEA, proposed new self-regulation guidelines, including demonetizing loot box prizes, providing values of prizes, etc., in 2015 (Choi, 2019). In contrast, the National Assembly proposed several drafts that regulate loot boxes, such as probability transparency (Bill 1914215, Bill 2000640, Bill 2002887). In 2017 and 2018, K-GAMES proposed amended self-regulation guidelines, providing probability transparency and expanding the regulation target to all video games.

1.1.6 Controversies around loot box

There are several controversies over loot box policy: declaring loot boxes as gambles, impacts on social benefits, transparency of odds, and self-regulation versus government regulation.

The first controversy regarding the loot box is whether it should be determined as gambling. Proponents argue that the loot box fulfills common conditions of gambling, as proposed by Griffiths (1995): the exchange of cashable things for an uncertain prize until a certain future event, coincidence of the event that concludes prize, unproductive redistribution of wealth, and excludability of participant from risk by

absence. (Griffiths, 2018) They defended the objection that the usual prizes of loot boxes are in-game items without cash value, arguing that third-party carriers provide exchanges of virtual items into cash value as an example. (Abarbanel, 2018) In contrast, opponents criticized the former's argument stating that by their criteria even ordinary activities with risks, such as stock market trading or investment are counted as gambling. (Abarbanel, 2018) They categorize activities as gambling in video games only if they are simulations of real gambling or involve the staking of real currency or cashable items. The framework of Parke, Wardle, Rigbye, and Parke (2012) is one of the taxonomies that defends the loot box from being determined as gambling. According to this framework, a loot box is not gambling because of the following points: one cannot win real money, they do not represent the core of the game, and do not simulate casino activities. (Koeder, Tanaka, and Mitomo, 2018) Thus, opponents, such as ESRB or Pan European Game Information, the European video game rating organization, categorize loot boxes as an in-game item purchase system rather than gambling. (Hood, 2017)

There are pros and cons of the impact of loot boxes on social benefit. Proponents argue that a freemium model, such as a loot box, will increase social surplus by price discrimination; consumers with a higher willingness to pay gain more utility by additional consumption, while suppliers gain

additional profit from price discrimination. In addition, they consider that the uncertainty of the content of a loot box reduces performance inequality between the paid user and the free-gaming user. This will lead to a reduction in the price level of the game and an increase in users, which will increase utility for the users due to network externality. (Yoo, 2016b) However, opponents criticize the uncertainty of loot boxes that leads users to increased overconsumption of items than expected, and an addiction similar to that of gambling. (Choi, 2018) They found that the cause of overconsumption of loot boxes originated from two effects: denomination effect and preference reversal. (Yoo, 2016a) As loot box systems mislead the consumer about the expected price using uncertainty, the consumer becomes less resistant to spending money, which leads to overconsumption, according to the opponents. Moreover, as Slovic and Lichtenstein (1983) verified, people do not decide based on the expected utility and act rationally, as expected by utility theory (von Neumann and Morgenstern, 1944). Instead, they decide heuristically based on the utility of the prize and the odds. Thus, according to the opponents, the provider may distort consumer decisions, using a loot box, to increase their profit.

Disclosure of loot box probabilities is an important issue. The pro-regulation group indicates the problems caused by the concealment of odds: repetitive and excessive consumption and probability manipulation. Thus,

they urge that the revealing of the odds should be defined as a consumer right. (Park and Lee, 2018) In contrast, opponents of regulation refute that users can predict the odds despite an absence of information and consume game items rationally. They consider the game market to be a perfect competitive market with no barriers and a wide variety of providers. Therefore, a consumer may switch to another provider if a loot box is not beneficial, and thus, the odds will be maintained at an equilibrium level. They defend the providers in that the odds of loot boxes should be considered as an industrial secret, similar to profit margin, and its confidentiality should be secured to provide freedom of business. Furthermore, opponents are concerned with the cascade effect: a few irritated consumers instigating others to irrational choices. (Yoo, 2016b)

There is a debate between self-regulation and legal regulation. Proponents of self-regulation criticize government regulations in that they cannot respond promptly. This is because the online industry can rapidly determine the loopholes in regulations by vague revisions. (Park and Lee, 2018) In contrast, opponents indicate that self-regulation in the game industry does not work properly, as it has already failed in South Korea, and the self-regulation board cannot be responsible for all providers while they are not expert on video game regulation. (Choi, 2019)

1.2 Problem description

Several studies have already indicated the probability disclosure issue in loot boxes. However, most of the research only describes probability transparency as a policy in loot box regulation. (Nielsen and Grabarczyk, 2018; Koeder, Tanaka, and Mitomo, 2018; Korhonen, 2019) Others, which studied the effects of loot box odds disclosure, studied the administrative (Choi, 2019; Choi, 2015), or the economic perspective. (Chen et al., 2019; Yoo, 2016b) Authors of papers written from an economic perspective studied how a transparency of odds would affect the video game market. Chen et al. (2019) proved that distorting loot box allocation would increase the provider's revenue, even if the supplier keeps the total allocation ratio but differentiates each user's allocation; leaving a solution of the odds manipulation issue to future works. In contrast, Yoo (2016b) criticized the disclosure policy, highlighting a negative cascade effect, and proposed a laissez-faire policy; however, the study did not provide empirical evidence for its suggestion. Another limitation of previous studies taking an economic perspective is that they focused on long-term effects, as they assumed an equilibrated market. However, as the product life cycle in the video game market is short and continues to shorten (Seo, 2019), especially in case of the mobile game market in which loot box marketing is popular (Lee, 2014; Lee, 2016), developers focus on short-term

revenue, neglecting long-term effects. (Kim, 2015) Therefore, the effects and measures of disclosing odds from an economic perspective, and the short-term effects of loot box probability information distribution on the video game market should be examined when drafting loot box odds transparency policies.

1.3 Research objectives and research questions

The objective of this research is to analyze the diffusion of information on probability allocation in loot box systems and fluctuations in revenue caused by firm allocation manipulation during the diffusion process.

There are two research questions to be answered in this study. One is whether we can estimate the loot box provider's profit from probability manipulation. The other is how different factors affect the information diffusion process, such as the structure of the user's network, reliability of information, and process of information collection.

1.4 Methodology

In this study the research objectives were investigated using agent-based model simulations. Although differential models, such as the Bass model (Bass, 1969) are popular in diffusion studies, the differential model

is not appropriate for our study because it cannot analyze the effects of the factors this study is concerned with: network structure, information confidence level, and information gathering process.

1.5 Outline of paper

We will review previous articles that analyzed loot boxes and diffusion using agent-based model simulations in Chapter 2, and discuss the set-up of the model in Chapter 3. Experimental setup are given in Chapter 4. The results of the simulation of the constructed model are given in Chapter 5. We present the conclusion in Chapter 6.

2. State-of-the-art

2.1 Loot box

2.1.1 Studies on loot box

Koeder, Tanaka, and Mitomo (2018) reviewed discussions on loot boxes and Gacha systems by explaining the concept of a loot box and Gacha, and reviewed the present state of international regulations, and surveyed user on the effects of microtransactions on game ratings. The research concluded that the transparency of loot box allocation should be considered for determining if the loot box constitutes a gamble or not by a regulation

body, and more studies on consumer and provider behavior regarding loot boxes should be conducted. Nielsen and Grabarczyk (2018) suggested renaming loot boxes to “random reward mechanisms (RRMs)”, and explained the history of RRM, the relation between RRM and gambling, and the taxonomy of RRM. They concluded that RRMs have many features that gambling has, but only a few of them could be defined as gambling. Yoo (2019a) reviewed the history, issues, and regulations of the loot box. The article was concerned with the characteristics of the loot box, which lead to overconsumption; however, it warned of impetuous regulations without a mature review of the effect on social benefits and details of the loot box.

2.1.2 Studies from an economic perspective

Chen et al. (2019) built a mathematical model to analyze the revenue of a loot box. In the paper the analysis of 4 selling models is described, including 2 loot box selling models and a comparison of their maximum revenue. It was determined that one loot box model may absorb all consumer surplus and gain more revenue. In addition, the authors expanded the analysis to multi-item loot boxes, discrimination of prizes by class, transparency of allocations, and a refund system. The limitation of this study was that independent consumers determined consumption decisions based only on price and odds information; thus, more studies are

needed, particularly studies including a social network perspective and information inequality.

Lee and Yoo (2016) analyzed the effects of loot boxes on user's in-game item consumption and in-game inequality. They concluded that loot boxes may increase the expense of users with low or high incomes and decrease in-game inequality. Extending from the above-mentioned research (Lee and Yoo, 2016), Yoo (2016b) analyzed the effects of the loot box on changes in a video gamer's utility, and the logic of the revised loot box regulation proposal based on an economic approach. The report determined the loot box to be a price discrimination strategy that increases social surplus. It claimed that a loot box may increase the utility of video game users by resolving inequality among heavily-charged users and lightly-charged users and increases free-gaming users, assuming a positive network externality. It also criticized probability revelation due to the negative cascade effect, while insisting on the futility of profit-maximizing odds manipulation in the long term, as the video game market is a perfect competitive market and consumers may shift to other games. This paper suggested a ground-breaking market analysis of the gaming industry: a perfect competitive market that does not maximize social surplus and in which producers can absorb consumer's surplus and dead-weight losses by price discrimination, which can be obtained only in an

imperfect competition market. However, this study analyzed only the long-term effects of probability distortion, short-term effects should be analyzed as well due to a shortening of the product life cycle in this industry. In addition, the magnitude of the negative cascade effect and information asymmetry should be analyzed quantitatively.

Briest et al. (2015) examined the optimal mechanism for merchandizing lottery under given conditions, such as known consumer valuation distribution, monopolist provider, and plural types of substitutable items on sale. The results showed that a lottery system earns more revenue than a standard marketing system, especially if the number of the type of product sales is higher than 3. However, they found that the algorithm to find the optimal price of a lottery with a given consumer behavior distribution and probability is too complicated. This study may provide a meaningful contribution to the optimization of loot box systems and examines why video game providers prefer loot box systems to in-game item selling by proving the existence of additional revenue from the lottery system. However, the assumption that the price of the lottery is given endogenously when the probability is given exogenously is not appropriate in a reality, in which a provider sets the price of the loot box first and then sets the probability.

2.1.3 Studies from the legal perspective

Korhonen (2019) analyzed the legal regulations of loot boxes based on de lege lata and ferenda perspectives. The thesis examines loot boxes in view of marketing laws and investigates whether a loot box constitutes gambling under Norwegian regulations. This suggests amending lottery law to define loot boxes as de facto gambling, or self-regulation. Abarbanel (2018) reviewed the debate on whether loot boxes constitute a gamble or not; the paper concluded that considering loot boxes as gamble is immoderate, from a legal perspective. Griffiths (2018) reviewed various insights of international regulatory bodies on whether a loot box is a gamble. He found that the view is divided and that loot boxes should be considered to constitute a gamble because its expected output is lower than the price level. Hwang and Shin (2014) reviewed Japanese regulations on "Kompu Gacha", one type of loot boxes, with a comparative legal perspective, and analyzed whether the current law is able to regulate loot boxes. They concluded that Japanese regulations focused on consumer protection and fair trade, due to a self-regulation system on rating. They suggested executing current regulations on gambling and rating for the Korean case, as Korean law is already available to regulate them.

2.1.4 Studies from an administrative perspective

Park and Lee (2018) reviewed South Korea's legal regulations and self-regulations on loot boxes. They found that self-regulation seemed to be more efficient than legal self-regulation. However, suspicion caused by the failure of the 1st self-regulation draft and the inherent risks in self-regulation makes compulsory self-regulation the most feasible alternative to adopted regulation. Choi (2015) analyzed the controversies surrounding loot boxes and possible solutions. The paper stated that some controversies regarding loot boxes are overestimated and that loot boxes should not be considered as gambling, as the overconsumption issue is exaggerated. The author suggested investigating the effects of current loot box self-regulations, and not to execute legal regulations as this destroys the ecosystem of the industry. Choi (2019) analyzed the appropriateness of loot box self-regulation from an administrative perspective. The study showed that current self-regulation in South Korea does not execute the advantages of self-regulation, such as professionalism, efficiency, and flexibility. It argues that the existing self-regulation is oppressive self-regulation developed to avoid legal regulation.

2.1.5 Studies from a managerial perspective, case study, and survey

Jo and Ryu (2019) studied the structure and regulation of "double loot boxes". They revealed that this model makes it difficult to monitor odds distortion; thus, allocation transparency monitoring policy should be studied. McCaffrey (2019) evaluated loot box self-regulation from a managerial perspective. The study explains current legal and self-regulation attempts and examines how the self-regulation policy hedges consumer harm and improves user-developer relations. Alonso and Jigvall (2018) collected opinions on loot boxes from various focus groups and analyzed them based on current research outcomes. They concluded that there are few studies on loot boxes and loot boxes should be considered as design methods.

2.2 Agent-based model simulation of diffusion.

Kiesling et al. (2012) reviewed articles on agent-based model simulation of innovation diffusion. They classified articles based on their findings on agent-based modeling, theoretical outcomes, and practical applications. The authors suggested that more research is needed on the agent-based model assuming repurchase, and a model integrating the diffusion of innovation and competition between providers should be

developed. Some of the articles that had been reviewed by Kiesling et al. (2012) provided a theoretical background for this research.

Several studies have compared different types of networks on innovation diffusion. Alkemade and Castaledi (2005) compared the diffusion of innovation in regular, small-world, and random networks, varying network density and they found that the cascade effect appears more often and the threshold of exposure increases with lower density, and that small-world and random networks have similar threshold levels. Kuandykov and Sokolov (2010) compared diffusion in scale-free and random networks, assuming adoption probability is determined by the neighbor's adoption ratio. The result showed that random networks cause faster diffusion, especially in "cluster random networks".

3. Model

In this study, the diffusion of information in a network of game users is considered. The aim is to analyze how the revenue of the loot box fluctuates due to diffusion of information on item allocation policies in diverse scenarios and assumptions, and if the policies we suggest will work properly or have unintended side-effects. In the model, we assume that the loot box market consists of a massive number of consumers connected via social networks and a monopolist game service (and loot box item)

provider. The provider may tilt the allocation and probability policy of the loot box from the probability it has stated to users. Information about the tilted policy is diffused after it has leaked or been identified.

3.1 Game users

This model assumes that every game user decides the amount of loot box consumption based on their willingness to pay for in-game items, given the price of the loot box, and given the acquisition probability of the items. In each period, users may purchase loot boxes similar to sequential buy-many models, as Briest et al. (2015) suggested. Consumers purchase a single loot box and release it, and then, decide whether to purchase an additional box. For simplicity of the model, users are assumed to behave myopically and risk-neutral regarding the purchase of a loot box. Although myopic behavior may not be optimal, the assumption is accepted for two reasons: users' behavior in the real world fits myopic behavior better than the optimal one, and it is asymptotically optimal. (Chen et al., 2019) However, the myopic purchase model is still not appropriate for agent-based model simulations, as consumers may buy the box infinitely often while the expected utility exceeds 0, and as the expected utility is fixed, users may buy loot boxes eternally and infinite loops may occur. Thus, the model needs to set a limitation for expense; here, it is assumed that users

will stop buying the loot box if the cost exceeds their valuation of the item. Then, user i will decide to purchase an additional loot box if the user is yet to win the item; the total expense of the current term is less than the user's willingness to pay, and as in Formula (1), with U_i: expected utility of user i, π: probability of winning the item, w_i: willingness to pay for the item of user i, p: price of loot box.

$$U_i = \pi w_i - p \geq 0 \quad \cdots\cdots\cdots\cdots \text{Formula (1)}$$

The willingness to pay (WTP) of each user is exogenous and independent of other factors. This assumption fits if the in-game items are cosmetic (Chen et al., 2019). The distribution of the customers' valuation of the items is assumed to be exponential and this assumption is supported by a survey on loot box expenditure by Zendle and Cairns (2018), and Brooks and Clark (2019).

Regarding propagation of information, the model assumes that information is adopted probabilistically, that is, informers spread their information on odd manipulation of their neighbors, and the neighbors randomly adopt the information and spread the information in the next term.

3.2 Provider

The provider is assumed to be a monopolist for simplification of the model. Although Yoo (2019b) modelled a loot box market as a perfect competition market, the assumption still holds because of the existence of several market environments. In the video game market, providers construct entry barriers to protect their users by differentiating the service by developing their own IP (Intellectual Property) or collaborating IP franchise. In addition, the positive network effect also acts as an entry barrier. Therefore, the assumption still holds because the user will stick to the provider's game service unless the harm of probability manipulation exceeds the provider's entry barrier. The provider's marketing strategy follows Chen et al.'s (2019) normal loot box model. Simplifying the model, this model assumes that the provider sells a loot box that provides only one type of item with probability $0 \leq \mathrm{p} \leq 1$.

The provider sets the probability allocation policy as follows: it publishes price π and the probability to win the item p(official probability), setting the loot box system to offer the item with a probability of p'(real probability), which follows $0 \leq \mathrm{p}' \leq p$. It will maintain their tilted allocation policy until the expected revenue with official odds exceeds their current revenue with manipulated odds. The provider determines the manipulation of the probability based on last term's revenue and it stops probability

distortion if last term's revenue is less than the revenue with official odds.

The expected revenue is calculated with the information on the spending behavior of users and their distribution of willingness to pay. As mentioned in Section 3.1., users will buy the loot box if the expected utility $U_i = \pi w_i - p \geq 0$ until they win the item or their expense exceeds their willingness to pay w_i. Ignoring the last assumption, in which consumers will stop buying the loot box when their expense exceeds their willingness to pay, the expected expense X_i for each user i is given by Formula 2.

$$\mathrm{E}(X_i) = \begin{cases} \sum_{n=1}^{\infty}(1-\pi)^{n-1} \cdot p = \frac{p}{\pi} \ (\pi w_i \geq p) \\ 0 \ (\pi w_i < p) \end{cases} \quad \cdots\cdots\cdots\cdots \text{Formula (2)}$$

Adopting the last assumption, the term that describes expense above the willingness to pay should be excluded, as in Formula (3) with $(n = [\frac{v_i}{p}])$.

$$\mathrm{E}(X_i) = \begin{cases} \sum_{k=1}^{n}(1-\pi)^{n-1} \cdot p = \frac{p(1-(1-\pi)^n)}{\pi} \ (\pi w_i \geq p) \\ 0 \ (\pi w_i < p) \end{cases} \quad \cdots\cdots\cdots \text{Formula (3)}$$

As the model assumes that the provider knows only the mean of the distribution of the WTP, but not the exact distribution, the initial revenue will be modelled by the Monte Carlo method, calculating each $\mathrm{E}(X_i)$ with randomly produced w_i.

3.3 Structure of network

Owing to the lack of previous studies on video game users' social networks, it is difficult to assume a certain structure of a user's network. Thus, this model will investigate 4 probable types of social network structures: random networks, regular networks, small-world networks, and scale-free networks. These structures were selected, as previous studies used these to study diffusion in social networks (Kiesling, 2012; Alkemade and Castaledi, 2005; Kuandykov and Sokolov, 2010; Koohborfardhaghighi and Altmann, 2016). Simplifying the model, we assume that the user network is static, as the spread of the information is sufficiently fast and the term of the situation is short enough to ignore the transformation of the network.

3.4 Diffusion process

Diffusion is executed by the network's feature, provider's marketing policy, and deviations in consumer behavior, such as willingness to pay. In the model, each agent acts as the table below each time. The network's features, official and tilted odds of the loot box, and consumer behavior are given exogenously and fixed. The consumer's purchase quantity, provider's revenue, and dispersion of probability information are

endogenous, which depends on the exogenous variables above and the actions of the agents. Simulating this model, in this study, the short-term surplus revenue of the provider is analyzed by probability distortion, and the effect of the network structure and provider's probability policy on revenue. Table 1 gives a brief overview of the method of model diffusion.

Table 1. Operation method of model diffusion

Each period of simulation:
1. Provider decides whether to maintain their probability manipulation policy, based on the current revenue and expected revenue when odds are not manipulated.
2. Users with probability information let their neighbors know about it.
3. Users decide their amount of loot box payment discretely based on their information; they can only choose between two payment options: optimal consumption based on official probability information or probability information according to rumors.
4. Provider calculates their revenue.

3.5 Reliability of distortion information

Information on loot box allocation probability may be leaked by a deep throat, or it may be revealed by gathering and processing information on item consumption and allocation data. In this case, the moment of information appearance is determined not exogenously, but endogenously depending on the users' expense and item allocation results. In addition, the decision of whether the users may adopt or propagate the information depends on the reliability of the information noticed, which depends on the

size of the allocation data and the level of distortion. The study assumes that the users will adopt the information and propagate it probabilistically, if the statistics show that the real odds will be more likely and the information's reliability is above their threshold, which is uniform for every user. To determine the confidence level of the information, the user needs three pieces of information: probability distribution of the loot box, number of loot boxes purchased, and number of wins. This study assumes that the user will approximate the real probability and then process and propagate the information on the real probability when the statistical test shows the real probability with a certain confidence level that exceeds the user's threshold. According to the loot box system, the number of prizes won follows the binomial distribution with mean $t\pi$ and variance $t\pi(1-\pi)$, while t stands for the number of loot boxes released, and π stands for the real probability. As a binomial distribution $B(n,p)$ can be approximated to the normal distribution $N(np, np(1-p))$ if n increases and p is not close to either 0 or 1, this model will use a normal distribution to determine the confidence level of acceptance of the probability based on statistics. To check the condition on n and p, the model will start the test when both $t\pi$ and $t\pi(1-\pi)$ are no smaller than 5. Based on their number of consumption t and wins w, each user tests the null hypothesis

$$H_0: w = t\pi \quad \cdots\cdots\cdots\cdots \text{Formula (4)}$$

against alternative hypotheses

$$H_a: w = t\pi' \quad \cdots\cdots\cdots\cdots \text{Formula (5)}$$

where π' denotes the announced probability. Then, the consumer will adopt the new probability information, if the probability that the new information is wrong, which is a type 2 error, is low enough. The probability that a type 2 error does not happen $1-\beta$ should be lower than the user's confidence level threshold c. A type 2 error can be described as follows:

$$\beta = \mathrm{P}(\mathrm{w} \leq \mathrm{k}\ \mathrm{when}\ \mu = \mathrm{t}\pi') = P\left(\frac{w-t\pi'}{\sigma} \leq \frac{k-t\pi'}{\sigma}\ when\ \mu = t\pi'\right) = P\left(\frac{w-t\pi'}{\sqrt{\mathrm{t}\pi'(1-\pi')}} \leq \frac{k-t\pi'}{\sqrt{\mathrm{t}\pi'(1-\pi')}}\ when\ \mu = t\pi'\right) = \mathrm{P}(\mathrm{Z} \leq \frac{k-t\pi\prime}{\sqrt{\mathrm{t}\pi'(1-\pi')}}) \quad \cdots\cdots\cdots\cdots \text{Formula (6)}$$

where k is the acceptance level of H_0, which is

$$\mathrm{k} = \mathrm{t}\pi + z_c\sigma = \mathrm{t}\pi + z_c\sqrt{t\pi(1-\pi)} \quad \cdots\cdots\cdots\cdots \text{Formula (7)}$$

(z_c: two-tailed standard normal value of confidence level c, which is the user's confidence level threshold).

3.6 Production of information

In this section, this study extends the assumption described in Section 4.1, criticizing the assumption on data production. Data regarding item allocation results may be gathered collectively, different to above, where it is assumed that data is collected by individual users. Collective data processing may accelerate the process of data collection and processing and will move the time at which the information is revealed forward. In this case, the study assumes that regulation authorities will indiscriminately gather all users' item allocation result data, and publish the processed odds statistics based on this data for all users. Users may decide their expense alternative based on the reliability of the information.

4. Experimental setup

4.1 Simulation environment

To study the model designed and analyze the diffusion dynamics and its factors in the model, a computational simulation on an agent-based model is executed. This study simulates the designed model using the programming environment of NetLogo (Wilensky, 1999). This environment is selected due to its simplicity for modelling and an abundant model library for applications. The model is built on the "Virus on a

Network" model (Stonedahl and Wilensky, 2008), which is part of the basic library of NetLogo. This model is selected as the model simulates diffusion in a static network, despite assuming diffusion of viruses, not information.

4.2 Parameters and settings in the simulation

Table 2. List of parameters and their values used in the simulation

Parameter	Value	Reference
Number of users in loot box market	1000	(Alkemade and Castaldi, 2005)
Average degree of nodes in user network	8	(Cole and Griffith, 2007)
Rewiring constant in small-world network	0.05	(Watts and Strogatz, 1998)
Number of initial nodes in scale-free network	9	(Kuandykov and Solokov, 2010; Cole and Griffith, 2007)
Number of seed links in scale-free network	4	(Kuandykov and Solokov, 2010; Cole and Griffith, 2007)
Price of single loot box	1	(Haile and Altmann, 2016)
Average willingness of users to pay	5	-
Official odds of loot box to win prize	20%	-
Real odds of loot box to win prize	0-18% (2% interval)	-
Information release point in exogenous information release scenario	100	(Haile and Altmann, 2016)

Confidence level threshold of user to adopt the information on real probability	0.9, 0.95, 0.99, 0.995, 0.999	Conventional setup in quantitative research

Table 2 lists the parameters used in the model simulation and the values of each parameter. Owing to a lack of computing power for the simulation, this model will set the number of users to as small as possible. The simulation uses 1000 users, as Alkemade and Castaldi (2005) used this size as their minimum for conducting an agent-based model simulation. To benchmark a real video game user's social network, this study sets an average node degree using an analysis on user's social network. According to Cole and Griffiths (2007), the average number of relationships gained by video games is 7. However, as this is an odd number, which makes it difficult to construct a regular network, in this study the degree will be rounded up, assuming the remainder to be an existing relationship before playing. Thus, this study will set the degree to 8 in a regular, random, and small-world network. The rewiring constant in small-world networks is usually set to 0.05 (Watts and Strogatz, 1998). The number of initial nodes and seed links in a scale-free network also follows the usual settings, wherein the number of seed links and initial nodes are as small as possible (Kuandykov and Solokov, 2010). To make the scale-free network's average node degree the same as those of other networks, here, the

number of seed links and initial nodes are set to 4 and 9 each, which generates the same total links as in other studies.

Simplifying the analysis, this simulation will set the price of a loot box to 1, following a previous study (Haile and Altmann, 2016). Due to the lack of analysis of the average probability of winning in the loot box, this study set the probability to win discretionally, i.e. it set 20% as the official probability to indicate the scarcity of the prize and set a range of real probability wide enough to set an interval. As the provider is able to earn additional profit only if they set the real probability lower than the official one, in this simulation the range of real probability is set from 0% to 18% with an interval of 2%. The provider may set the real probability as low as possible to earn additional revenue, or similar to the official one to prevent users from noticing the manipulation. By varying the real probability, in this study, the value of real probability that maximizes revenue based on the given factors is analyzed.

The time lag of information release is also set discretionally to 100 periods, which is long enough for the provider to enjoy profits from opaque selling. The probability to adopt is set at a rate that is common with previous research that assumed probabilistic adoption (Bohlmann, Calantone, and Zhao, 2010). The option threshold of confidence of information is set at a level that is common in statistics.

In the case of a random network, a spatially clustered network with random positioning of nodes is used for convenience of simulation. The simulation code develops a small-world network using the Watts-Strogatz model, with an exogenous value for the rewire probability and average degree. With regards to the scale-free network, in the study, the Barabasi-Albert model is used with exogenous numbers of initial nodes connected and connections per new nodes to construct it.

4.3 Scenario description

In this simulation, three scenarios were assumed: an exogenous information release scenario, a personal information analysis scenario, and a collective information analysis scenario. Table 3 shows features of each scenario in brief. The first scenario assumes that users cannot produce information on the real probability themselves but receive it from a deep thr at a given time. The period in which a user notices information given by a whistleblower is given exogenously. In a personal information analysis scenario, users try to analyze the real probability themselves. Each user gathers data on their loot box allocation results and statistically analyzes them. The collective information analysis scenario is similar to the personal information analysis scenario, however, it assumes that the regulation body compulsorily gathers all users' results and analyzes them.

Table 3. Summary of three scenarios

	Exogenous Information Release Scenario	Personal Information Analysis Scenario	Collective Information Analysis Scenario
Source of Info	Exogenous agent (Lee, 2018)	Personal user's analysis (Kim, 2017)	Regulator's analysis (Choi, 2019)
Information release time	100 ticks	When user detects manipulation	When regulator detects manipulation
Initial informed user	Randomly selected user	User who detected manipulation	All users
Condition of adoption	Randomly (50%)	Randomly (50%) if the information's reliability exceeds user's confidence threshold	Randomly (50%) if the information's reliability exceeds user's confidence threshold

4.4 UI

Figure 1 shows the simulator after setting up the model, and Figure 2 shows how the simulator works while operating the simulation. Each dot in the black box indicates a user, and the white line indicates the relationships between users. A user can set parameters using mint-colored boxes, sliders, and chooser on each side of the black box. The cream-colored graph shows the proportion of users and revenue for each period. The rightmost box shows the total additional revenue the provider has earned.

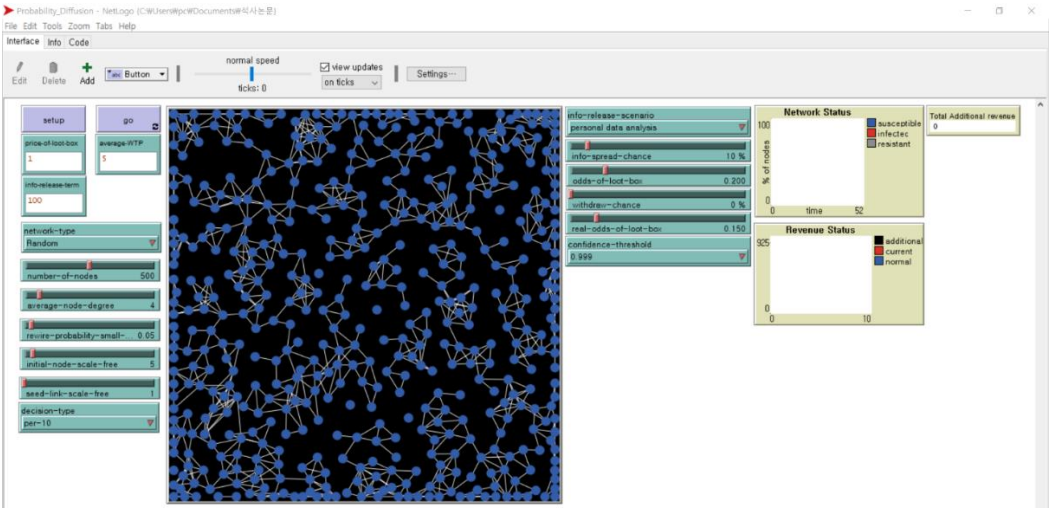

Figure 1. Simulator after setup

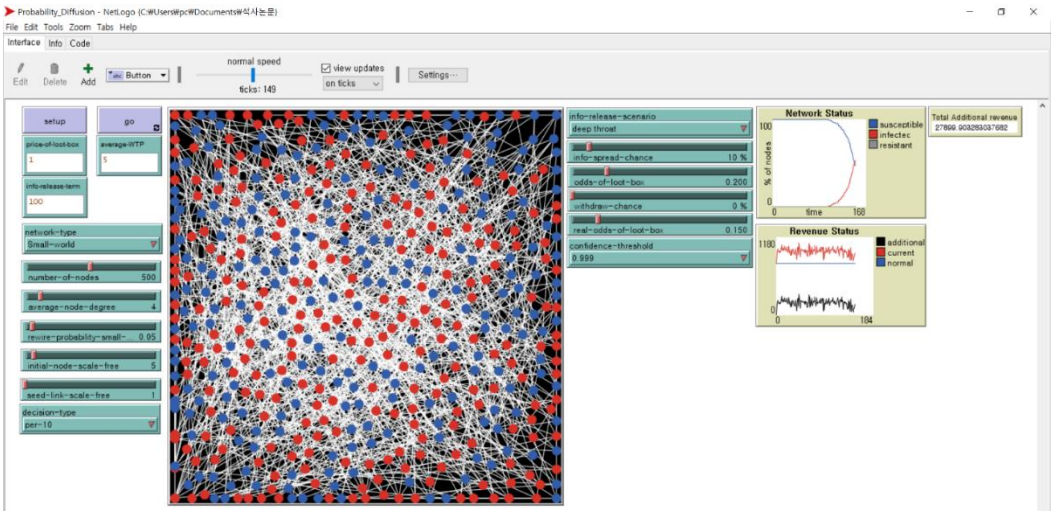

Figure 2. Simulator in operation.

In Figure 2, the blue dot shows the informed user, and the red dots represent users who are not informed. In the upper graph, the blue line shows the proportion of users not informed, the red line shows the

informed proportion. In the lower graph, the red line shows the provider's current revenue, the blue line shows the initial revenue, and the black line shows additional revenue, which is the gap between current and initial revenue.

4.5 Validation of simulation setup

The official probability and the average WTP were set to show the difference in revenue before and after the information spreads, and to analyze the diffusion tendency. Testing several values of probability and average willingness to pay, which maximize revenue with a given official probability, each value has been set to 0.2 and 5, which makes the expected utility of the loot box the same as its price, which is 1. The moment of information release in the exogenous information release scenario is set to 100, referring to Haile and Altmann's work (2016), and validated by several tests with the simulation showing that it is enough to show the impact of both, probability manipulation and information diffusion.

5. Results and analysis

Then, the duration from the start to the stop of the provider's manipulation (manipulation duration) and total additional revenue from the

provider's probability distortion on the experiment (revenue) is considered. The provider's manipulation duration is measured as the number of ticks from the simulation start to its end, when the provider notices that the revenue of the period is below the expected revenue calculated using the official probability, and decides to end the manipulation. Revenue is measured as the sum of each additional revenue, which is the gap between the revenue of the current period and the expected revenue with the official probability per period during the manipulation duration.

5.1 Simulation of exogenous disclosure scenario

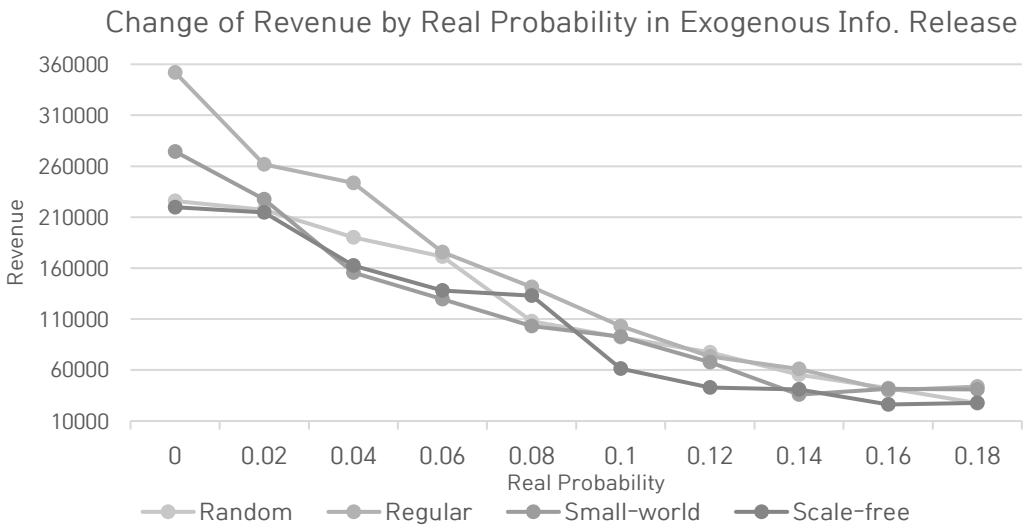

Figure 3. Graph of real probability and revenue of loot box in the exogenous information disclosure scenario

Figure 3 shows that there is a negative correlation between real probability and revenue, regardless of network type. Furthermore, it shows that the revenue in a regular network tends to be the largest, while it is difficult to find differences among the amounts of revenue in other networks.

The simulation results of this scenario can be analyzed by the exogeneity of information disclosure. As the information about the real probability is released exogenously, the real probability of the loot box does not affect the duration of the manipulation, but it does affect each user' s expenditure decisions. As a larger difference between official and real probability increases the user's expenditure, a smaller real probability earns more revenue in this scenario.

Figure 4 shows that the type of network makes a difference for the duration, while real probability hardly has an effect. The duration tends to be consistent regardless of the probability, while the duration by network type is ranked in the order of regular, random, small-world, and scale-free network from the longest to the shortest, respectively, except at the real probability of 0.18.

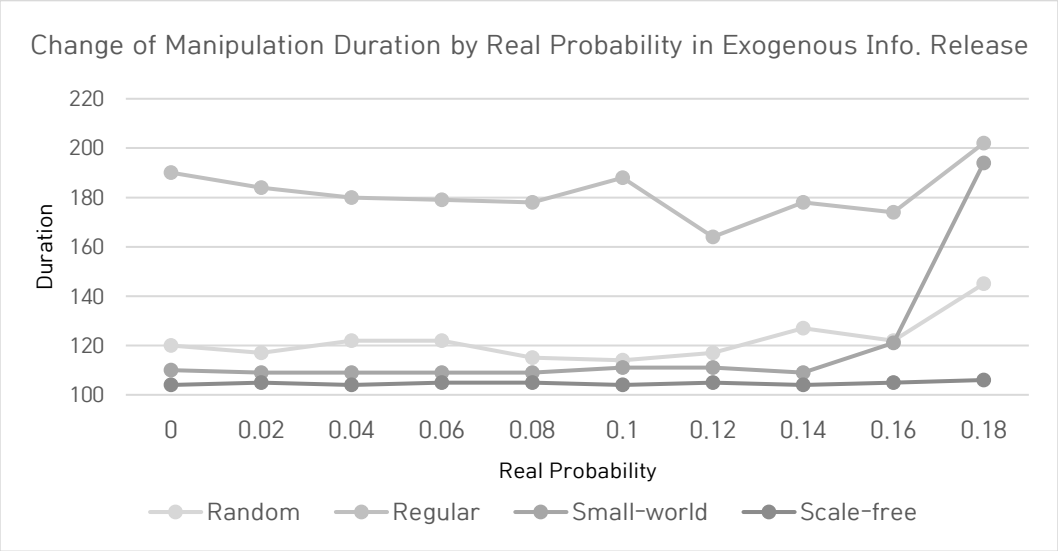

Figure 4. Graph of real probability and duration of manipulation in the exogenous information disclosure scenario

In this scenario, the differences in revenue and duration among different network structures can be analyzed by the features of the network structure. In the exogenous information release scenario, the time of information release is fixed, and thus both, revenue and duration depend on the speed of the information spread, which is related to features of the network, such as the average path length. As a regular network's average path length is longer than in others, its diffusion period becomes longer, and thus, the duration and revenue increase. Figure 4 shows that there is a trend in the duration among the random, small-world, and scale-free networks, ordered from the longest to shortest durations. The difference in durations between random networks and small-world/scale-free

networks can be analyzed by their average path length. As these two networks have short average path lengths (Barabasi and Albert, 1999; Watts and Strogatz, 1998), these networks are more sensitive to propagation of information in a timely manner. The difference in duration between small-world networks and scale-free networks may be determined by another feature of the network structure: degree distribution. In this model, the moment when the provider decides to cease the manipulation is determined by how much the revenue per period drops caused by information diffusion. Thus, the duration is determined by the moment when the majority of users are informed. In a scale-free network, in contrast to the small-world network, the degree distribution follows the power law (Barabasi and Albert, 1999). Therefore, it is easy for the majority of users to be informed once the hub user is informed and starts to spread the information. However, despite the difference in average path length among random, small-world, and scale-free networks, it is difficult to detect a significant difference in revenue among them because of the small size of the networks. Thus, more simulation and statistical analyses are needed to determine a significant difference in revenue among various network types.

5.2 Personal information analysis scenario simulation

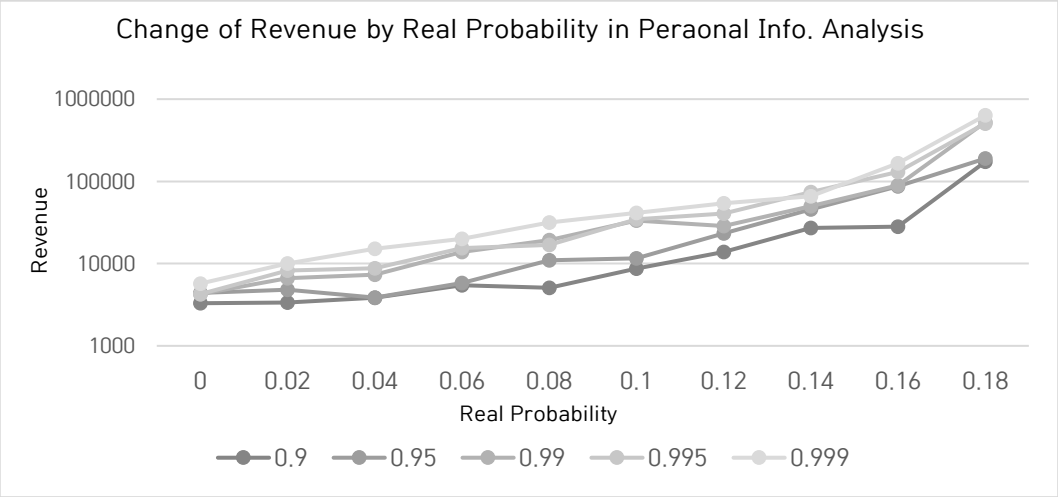

Figure 5. Graph of real probability and revenue in the personal information analysis scenario

Figure 5 shows the relationship between the real probability of the loot box and the revenue by various confidence thresholds in a scale-free network, in the personal information generation scenario simulation; the vertical axis is log-scaled. The reason why this simulation is currently only done in a scale-free network is the focus on the impact of information processing rather than the process of information diffusion. A scale-free network is selected because the simulation result in Section 5.1. showed that the diffusion speed of a scale-free network is the fastest and thus, the effect of the information diffusion process is relatively small. It shows two results: there is a positive correlation between the real probability and

size of the revenue and a higher threshold of information confidence tends to result in a larger amount of revenue.

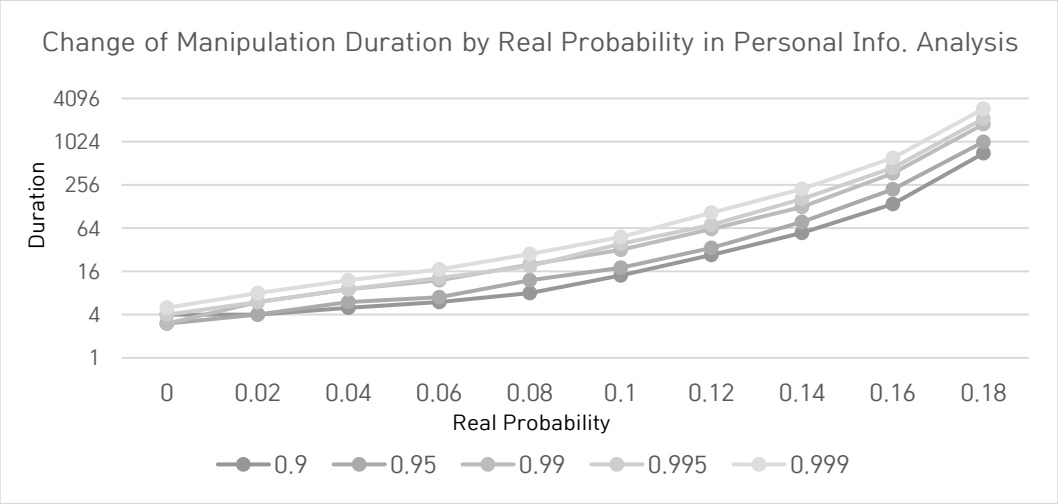

Figure 6. Graph of real probability and duration of manipulation in the personal information analysis scenario

Figure 6 shows the relationship between the real probability of a loot box and the duration of the probability manipulation with various confidence thresholds in a scale-free network, in a personal information analysis scenario, with a log-scaled vertical axis. It shows that the duration of manipulation has a positive correlation with the real probability and confidence threshold of information. The reason why the result is different from the first scenario is the endogeneity of the information release. As users need to collect sufficient data to inspect probability

manipulation, the loot boxes should be large enough to obtain information whose confidence level exceeds the user's acceptance level. Because the amount of loot box consumption to analyze the information increases as the manipulation is difficult to inspect with similar probability, a similarity in real and official probability increases the duration of manipulation. In addition, the result showed that the effect of duration increases exceeds the effect of larger revenue for each period.

The simulation results show that the length of the information process has a positive correlation with the duration of manipulation and size of revenue, as the confidence threshold of information and the difference between the official and real probability affects the length of the information process. Therefore, in this scenario, the provider should set the real probability to be as similar as possible and increase the user's information confidence threshold by promotion or media response, to delay the user's inspection process and maximize the revenue.

5.3 Collective information analysis scenario simulation

Figure 7 shows the relation between the real probability of the loot box and the revenue by various confidence thresholds in a scale-free network, in the collective information generation scenario simulation. It shows no relation between the users' information confidence threshold and revenue,

but a weak correlation between the real probability and the revenue. The revenue tends to increase as the real probability becomes close to 0 or the official probability.

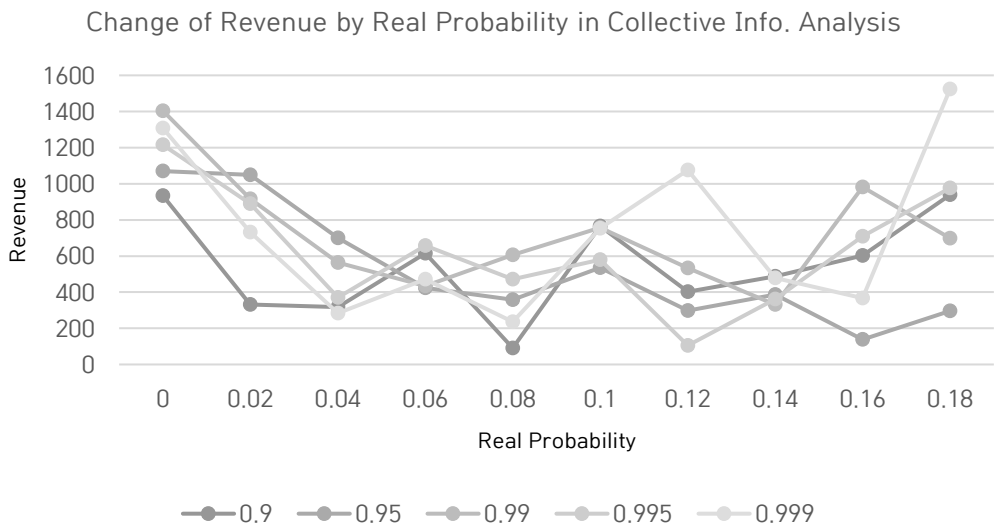

Figure 7. Graph of real probability and revenue in the collective information analysis scenario

Figure 8 shows a log-scaled graph of the real probability of the loot box and the duration of probability manipulation with various confidence thresholds, in a scale-free network, and in a collective information analysis scenario. It shows the duration of manipulation has a positive correlation to the real probability and confidence threshold of the information, while differences in duration caused by the information confidence threshold are hardly found.

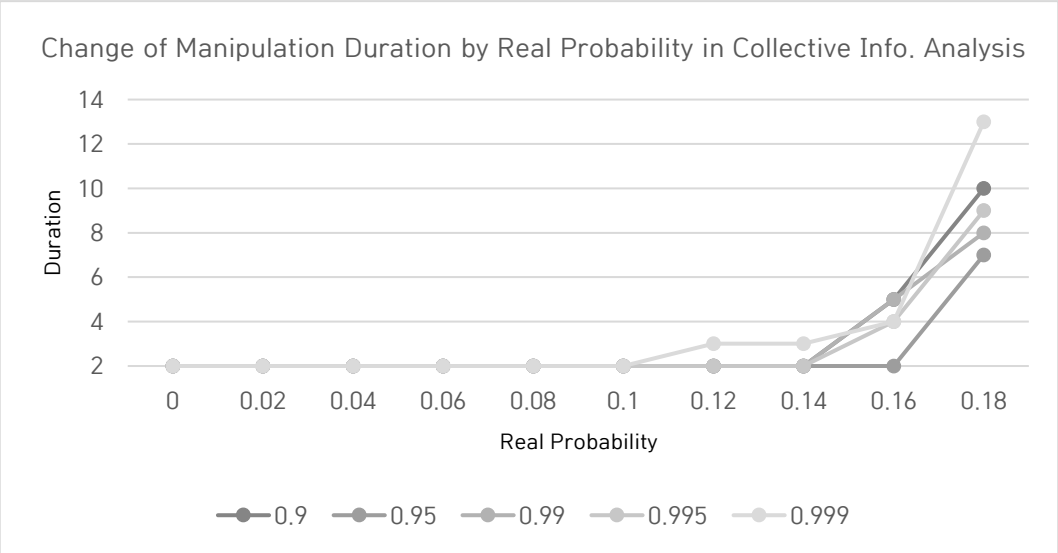

Figure 8. Graph of real probability and manipulation duration in the collective information analysis scenario

The result shows that the provider can take two strategies to maximize revenue in this scenario: one is to set the real probability to 0 despite the fast release of information, and the other is to set the real probability as close to the official probability as possible to make analysis more difficult and delay it. It is difficult to analyze the cause of vague differences in duration and revenue among various information confidence thresholds, but it seems that relatively short durations magnified the impact of factors randomly arranged, such as distribution of WTP, interrupted the result.

5.4 Comparison among scenarios

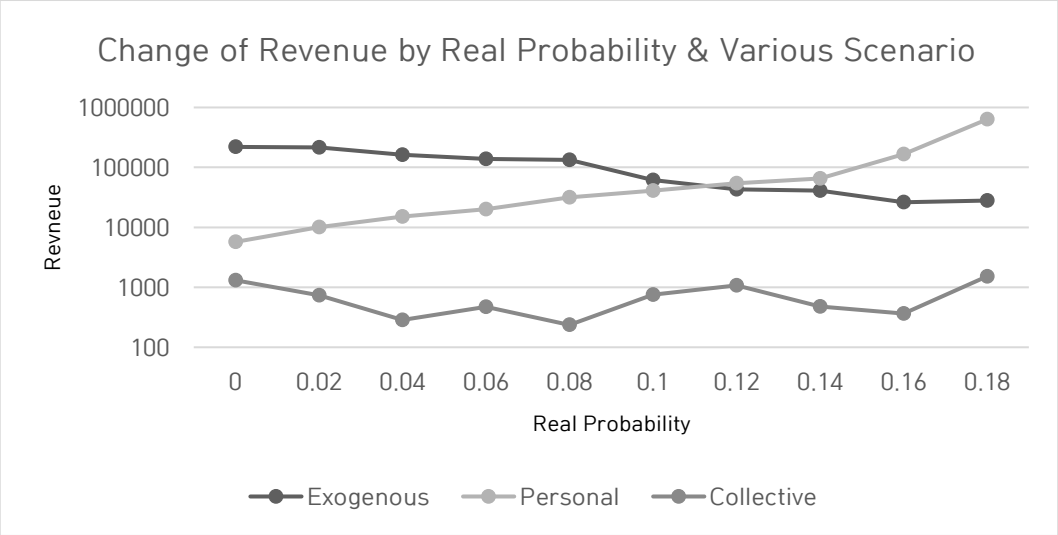

Figure 9. Graph of real probability and loot-box revenue in various scenarios

In Figure 9, the loot box revenue in different scenarios is compared in a scale-free network, with a log-scaled vertical axis. The information confidence threshold of the personal and collective information generation scenario is set to 0.999, as its revenue is largest. The result shows that the provider can earn the smallest revenue in the collective information generation scenario, regardless of the real probability. In addition, it shows that the exogenous information release scenario maximizes the revenue if the provider sets the real probability close to 0, and the personal information release scenario maximizes the revenue if the provider sets

the real probability close to the official probability.

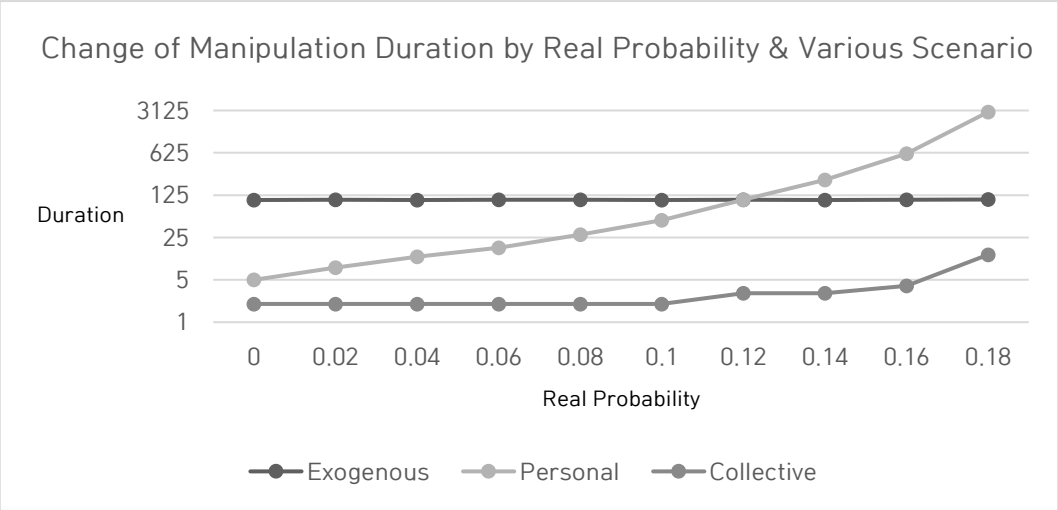

Figure 10. Graph of real probability and manipulation duration in each scenarios

In Figure 10, the manipulation duration in a varied scenario is compared in a scale-free network, with a log-scaled vertical axis. The information confidence threshold in the personal and collective information generation scenario is set to 0.999, as its revenue is the largest. The results show that the duration becomes shortest in a collective information generation scenario by a significant amount, while the exogenous information release scenario maximizes the duration if the provider sets the real probability close to 0, and the personal information release scenario maximizes the revenue if they set the real probability close to the official probability. The results show that the collective loot box result analysis minimizes the

revenue of the provider by manipulation as well as the duration.

6. Conclusion

This thesis contributed several insights to studies on loot boxes. First, it established an agent-based model that can estimate the revenue of a video game service provider by manipulating the loot box probability policy. This model estimates revenue based on the factors given by the provider, such as price and odds of loot boxes as well as user features, such as willingness to pay, network structure, and threshold for adopting new information. In addition, in this study, the effect of factors such as the structure of the user's network, reliability of information, and process of information collection in the loot-box market, on the information diffusion process and revenue is shown. If information is released exogenously, the revenue is maximized if the real probability is set close to zero; in contrast, the revenue is maximized if the real probability is set close to the official probability if information is released exogenously, by delaying the process of credible information of loot box probability and extending the duration of the manipulation. It also showed that network type affects the revenue and duration of loot box manipulation if the probability information is given exogenously. In the case of endogenous information generation, the study confirmed that the revenue increases with an increasing confidence

threshold of users for adopting information. In addition, the results show that a collective analysis of loot box trial results to inspect probability manipulation is effective; the analysis can curtail the duration of loot boxes by perceiving manipulation faster and thus, reduce additional revenue.

6.1 Policy implications

The results revealed that a video game service provider may gain short-term profit by manipulating the probability of the loot box, thus, supporting the regulation of loot box probability manipulation, and demands that regulation bodies do not only force the provider to declare the loot box probability, but also inspect whether it follows the published probability. As the model can estimate the revenue of a provider by probability manipulation, users may use the model to estimate the provider's unjust enrichment by manipulation in a suit for damages. The availability of estimations is useful as the provider does not want to reveal information on revenue to conceal business secrets. As the result showed that collective analysis of loot box allocation results can reduce the duration of manipulation and the additional revenue, a new alternative policy can be proposed in which regulation authorities force the revealing of the allocation results of loot boxes, rather than increasing legal regulation on it, such as enforcing official probability notice, or controlling price,

probability, or value of the prize of the loot box.

6.2 Limitations and future studies

Due to limitations in data and simplifications of the model, this study has several limitations. First, the model has not been validated and verified for a real case. As it is difficult to reveal loot box manipulation and any information on the provider's earnings is classified as a business secret, it is difficult to find the revenue data by probability manipulation. In addition, verification is omitted owing to limitations of the computation capability and data. Although the result is still meaningful as it shows qualitative results, the model should be validated by real manipulation results, experiments, or surveys (Haile and Altmann, 2016), and validated with repeated simulation and statistical tests.

Another limitation is the assumption of the users' behavior; this model assumes that the user consistently plays the video game service and purchases the loot box regardless of the manipulation, but users may withdraw from the service if they notice the manipulation (Pyeon, 2019). Future studies should consider withdrawal in the model.

The type of loot box is another limitation of the study. The model simplified the loot box model, but previous studies showed various types of loot boxes exist (Nielsen and Grabarczyk, 2018; Park and Lee, 2018;

Hwang and Shin, 2014; Koeder, Tanaka, and Mitomo, 2018), and Chen et al. (2019) constructed a mathematical model of various types of loot boxes. Future studies should expand the model to analyze the relationship between various types of loot box strategies and revenue.

The process of information generation also needs expansion, here, only personal analysis and collective analysis was considered, as authorities gather all users' allocation data and inform them of all results. However, users may spontaneously gather data and analyze it. Future research should analyze this case to confirm which policy is more efficient: forcing regulation bodies to collect users' loot box allocation data and analyze it, or not and leave the analysis to the user.

Researchers may expand the study to other cases of incomplete selling or information asymmetry, detecting deterioration of goods, fluctuations in stock prices, release of information, etc.

In contrast, researchers may expand the study by adopting new achievements from studies on the diffusion of innovations based on agent-based model simulations. For example, to expand the study from a static user group to a dynamic user group, we may import studies on learning organizations (Koohborfardhaghighi and Altmann, 2017), or strategic networking (Koohborfardhaghighi and Altmann, 2016) to study how a user network should be constructed to respond to providers' opaque selling.

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초 록

게임 시장의 주 수입원 중 하나인 확률형 아이템의 당첨 확률 조작이 게임 서비스 제공자의 수익에 미치는 영향과 이에 따른 정책적 제언을 놓고 사회적, 학술적인 논쟁이 있다. 이를 두고 여러 연구가 있었으나, 이들 연구는 장기적 관점에서 매출을 예상해 수명 주기가 짧은 게임 시장에 적절치 않고, 사회연결망 하에서의 정보 확산을 고려하지 않았다는 한계가 있다. 이를 극복하기 위해 본 연구는 행위자 기반 모형의 모의 실험으로 확률형 아이템 판매자의 확률 조작을 통한 이익을 추산하고, 소비자의 확률 추산 등의 변수가 이에 미치는 영향을 분석하고자 한다. 이를 위해 사회연결망으로 연결된 다수의 소비자와 독점 판매자로 구성된 행위자 모형을 세우고, NetLogo 상에서 모의실험을 진행할 것이다. 이를 통해 확률 조작이 단기적으로 안겨주는 매출을 계산할 수 있고, 집단으로 확률형 아이템 시행 자료를 수집했을 때 소비자가 더 빠르게 확률 조작을 인지할 수 있다는 사실을 확인할 수 있을 것이다. 이러한 결과는 확률 조작을 통한 게임 서비스 제공자의 부당이익을 추산하고, 확률형 아이템 관련 정책을 수립하는데 도움을 줄 수 있을 것이다.

주요어 : 확률형 아이템, 랜덤박스, 행위자 기반 모형, 정보 확산

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