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Measuring Industry Regulations Using an Agent-based Model: The Case of Online Games in Korea

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A B S T R A C T

As game industry prospers, the negative side of games becomes highlighted as well as its contributions to economy growth. In spite of strong arguments for the necessity to regulations as a means to decrease addiction or overindulgence, research has produced future suggestions rather than quantifiable evidence. In this paper, we propose adopting a simulation approach in addition to quantitative approaches to better understand optimal regulatory levels since a simulation approach can visualize unexpected side effects of regulations. In this study, we suggest the application of an agent-based model (ABM) as a smart service to measure the effects of regulatory policies. We review cases applying ABM in various domains and consider the possibility of using an ABM to understand the effectiveness of web board-game regulations. We find that the ABM approach would be useful in several areas, such as the analysis of regulatory effects that reflect a variety of characteristics, the measurement of micro-regulatory effects, and the simulation of regulations.

Keywords: Industry regulation, Agent-based model, Online games, Simulation study

Ⅰ. Introduction

Online games are an important part of Internet-based commerce. The market size of the Korean online gaming industry is over 8.8 billion USD. Web board games make up the largest share of online game sales based on their familiarity and simplicity. There are web board games look like Chess or Go in a form of player-to-plyer match with requiring substantial strategic thinking. To the contrary, we can also observe various web board games based on traditional card games like 7-Pocker, Blackjack and Hwatu (a kind of gambling popular in Korea and Japan) adding new features and items for more pleasure. Since card-based web board games share rules and features with traditional offline gambling,

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a learning barrier is relatively low.

Meanwhile, it should be noted that the Korean web board game industry has been shrinking continuously since 2008 when the government tightened regulations. For years, the Korean government has been strengthening regulation of online game services to protect young users from excessive spending and health problems. Currently, various online game regulations are enforced by the Korea Media Rating Board and the Ministry of Culture, Sports and Tourism. In particular, the Enforcement Decree of the Game Act, which has been enforced by the Ministry of Culture, Sports and Tourism since February 2014, does not allow a user to purchase more than 300,000 won of game money on a monthly basis, with a cap of 30,000 won per game. In addition, a user is banned if she or he loses over 100,000 won in a day by being denied access to any web board game for 24 hours. This shows that the online gaming industry has become the main target of industrial policy and regulation.

By contrast, little scientific research effort has been made to analyze how much of regulations on web board games are needed as compared to the needs and consequences of regulations. The sales and number of users of web board games have decreased significantly since the introduction of various gaming industry regulations. This major effect on the web board game industry contrasts with the limited quantitative analysis of regulatory effectiveness. It should be noted that even this effort has focused on post-regulatory analysis. The reality is that there is a lack of effectiveness analysis regarding regulations and regulatory changes in web board games, which is likely to confuse policy direction (Cookson, 2005).

In this study, as an alternative to analyzing the regulatory effectiveness of existing online games, we examine the agent-based model or ABM. In particular, this study highlights future challenges and directions of research in measuring the effectiveness of regulatory changes using new forms of a quantitative simulation method. This paper is organized as follows. First, we review the evolution of the agent-based model and organize the main concepts. Second, we examine the use cases of an agent-based model and finally consider whether an agent-based model could be applied to an analysis of online game regulatory effectiveness by way of regulatory effectiveness measurement.

Ⅱ. Agent Based Model

As computing power has developed, the ABM has been used in many fields of learning. The ABM has grown with the development of economic theory, computing power, and visualization technology.

2.1. ABM in the Early Stage

In 1948, in the early computer age, von Neumann presented the cellular automatic data model, which was one of the early attempts to apply ABM in research. Cellular automata models were initially used in biology, physics, and geography, but since then they have been combined with methods to implement micro and dynamic characteristics, which have also been used in social science. Later, efforts to analyze changes in individual factors in the model and identify changes in the system overall became more sophisticated as the performance of computers improved.

From a methodological perspective, Axelrod (1997) called ABM the third method of evaluation, different from the inductive and deductive logic systems of conventional social science. ABM was typically used to prove the decoupling model in social science (Schelling, 1971). Furthermore, in the field of natural science, computer engineer Reynolds also worked on ABM to understand the migration patterns of a herd of animals by reproducing behaviors using the Biods program in 1986. Since the late 1990s, however, rapid advances in computing technology and capabilities have allowed ABM to implement models that significantly improve the level of real-life reflection, enabling it to use the basis of social science and natural sciences as well as engineering tools to proliferate across a variety of scientific fields.

2.2. Features

ABM is a model for analyzing macro-level results caused by micro-level changes, which aims specifically to build the model in a top-down manner, such as identifying the characteristics of an agent and defining the interaction between an actor and the environment (Berger, 2001). This may lead to detailed observations of the actors and the environment in which the model is targeted, the analysis of data, or the evaluation of theoretical assumptions and their rationality.

ABM differs from conventional social science studies, such as logically weighing the assumptions contained in the repair model or verifying the validity of the assumptions with real data (Miler and Page, 2009). Researchers are relatively free to construct bottom-up models and overcome some of the limitations of the analytical models of traditional economic approaches by increasing data access through big data and computing-based studies (Williams, 2007). It should be noted that ABM was developed based on several social and natural sciences theories to account for the aspects of changes occurring within the system, considering interactions between multiple actors. As the ABM name suggests, the modeling technique focuses on relationships between actors. The economic approach, which is used as a representative quantitative analysis technique in the field of social science, requires mathematical analysis based on relevant data to understand socioeconomic phenomena. Nevertheless, this approach faces limitations that do not adequately predict economic changes that occur in practice (Williams, 2007). These limitations are built around conventional, historical data, resulting from structural problems of post-existing analysis, which lack the predictability and explanation of problems that have never been experienced. In other words, ABM has a relatively high degree of freedom in the analysis of economic rules and the interaction between actors, and external environments.

2.2.1. Actor

The actor defined in economics refers to a microeconomic entity that is mainly classified into a household, a company, or a government (Miler and Page, 2009). ABM allows a variety of actors to be defined, as each economic entity can be considered as a group or be further divided into sub-categories. In terms of actual programming, variables and functions are not considered as actors. Generally, it would be appropriate to understand that only objects capable of self-control and autonomous interaction are identified as actors. In this study, the actor is regarded as an autonomous decision-maker who wants to maximize economic utilities by learning from the environment and other actors in the context of a web board game.

2.2.2. Behavior Rules

Behavior rules are probabilistic or conclusive rules that determine an actor's behavior. In an ABM simulation, we assume that an actor has a set of explicitly known action rules (Miler and Page, 2009). In addition, the actual behavior that occurs according to the rules is regarded as either deterministic or conclusively determined. In addition, the question of which action rules will be applied may either be entirely arbitrary, the result of interactions with other actors, or the result of interactions with the environment. When building a model for analyzing the regulatory effectiveness of online games, action rules are implemented through the operator's decision-making system, with different rules of conduct for each given scenario after considering the high complexity of environmental issues.

2.2.3. Integrations

Interactions within the ABM can be defined as final outcomes that have undergone learning and adaptation processes, an intermediate outcome characteristic that is influenced by acts and feedback made directly and indirectly between actors (Miler and Page, 2009). Direct interactions result in the outcome of an action performed according to each defined action rule affecting the decision-making system of another actor, leading to arbitrary behavior. Indirect interaction refers to the effect of an actor's actions that causes a change in the external environment surrounding another actor, and again, a change in the behavior of another actor. This kind of interaction is represented by an iterative simulation structure within an ABM.

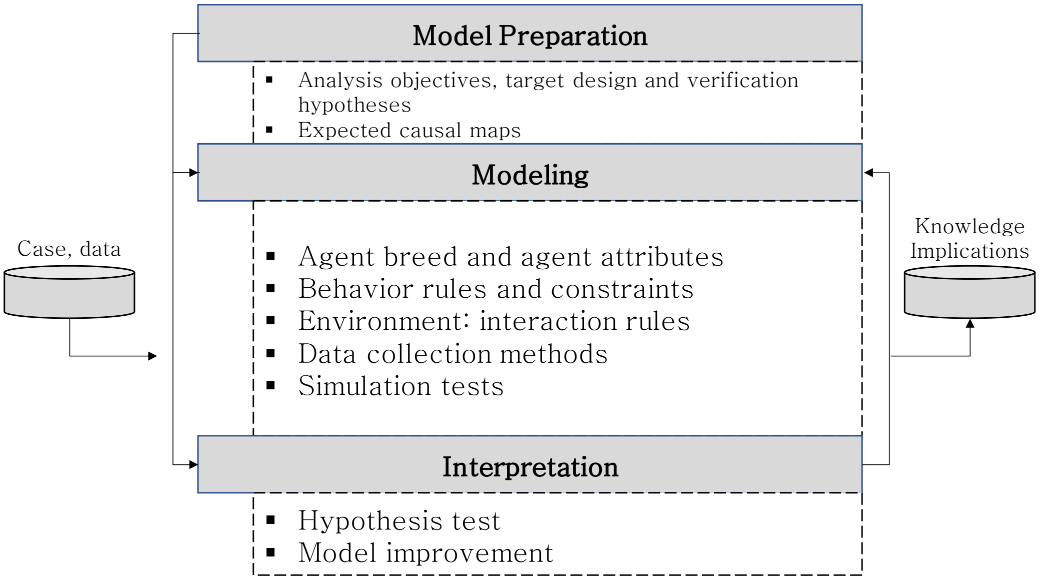
2.2.4. Environment

In ABMs, the environment is defined as the spatial concept in which interactions with the actor's arbitrary actions occur (Miler and Page, 2009). It could be described as a realistic space in terms of an actor making decisions in a given external environment or a conceptual space built within an analysis program. It is also depicted by obstacles or resources affecting actors' decision-making or inactive elements which are restricting actors' behavior.

In the analysis using ABM, researchers have expressed or overlooked the construction of an external environment too simple for the purposes and technical limitations of the study (Gilbert, 2008). Because it is not easy to identify all the complex external factors, a simple description of the environment around factors that have a significant effect on the agent has been accepted. However, it is true that the environmental composition based on researchers' assumptions can be arbitrary, and there is a danger of underestimating the reality. It appears that prior activities are necessary to try and validate the environment as accurately as possible based on an analysis of actual cases.

Ⅲ. Model

The ABM should be built with a clear design regarding key elements such as actors, behavioral rules, interactions, and environments. Compared with conventional economic analysis methods, the ABM can construct models for analysis, thus providing a relatively free representation of the actual social structure (Boero and Squazzoni, 2005). In addition, the size and direction of complex interactions can also be arbitrarily constructed, enabling results to be viewed from various perspectives (Bonabeau, 2002). Another characteristic of ABM is that it is possible to achieve inventive results by identifying the effects of new interactions. To fully explain unexpected analysis re-



<Figure 1> Designing an ABM

sults, it is necessary to design the model according to a structural analysis procedure. Unless sufficient theoretical grounds or empirical clues are supported, preceded by constructing a model, interpretation of the results can be difficult or mundane, which limits implications (Boero and Squazzoni, 2005). Although the structure and form of the agent-based model vary depending on the purpose and subject of the analysis, it generally follows the procedures illustrated in <Figure 1>.

An ABM can be applied to conducting a study for theoretical exploration of results from hypothetical models, or exploring a quasi-empirical event based on theoretical hypothesis with empirical descriptions, or developing an empirical-predictive machine for reasoning real world consequences based on a sophisticated simulator (Boero and Squazzoni, 2005). Using ABM for theoretical exploration can support real data that supports mathematical reasoning about what logical and theoretical issues will be revealed in the real world by simulation (Kang et al., 2007). If ABM is used for the purpose of observing quasi-experimental events, it can be used to validate policies with the benefit of determining the actor's behavioral assumptions at a realistic level based on existing data and then viewing the results of different variable scenarios. Also, ABM for empirical-predictive machines can be useful in understanding changes in future situations, requiring more sophisticated design and accurate parameter inputs compared with ABM for theoretical exploration or near-realism observation purposes. Overall, ABM provides a realistic and appropriate solution to problems that would be realistically expensive and time-consuming.

The transport sector is one of the areas in which modelling-based studies are actively conducted to establish relevant public policies. In particular, ABM is suitable for simulation analysis in areas where there are multiple interactions among various actors, such as developing urban spatial plans, improving public transportation systems, redesigning traffic mitigation plans, and analyzing the effects of new roads. In other words, studies in the transportation sector mainly target the analysis of traffic flows and the interaction of various mobility methods, considering the unique characteristics associated with the movement of pedestrians and vehicles.

While the study of pedestrians in the transportation sector remained under-researched in comparison with that of other means of transport, the enhancement of computer simulation has changed the situation (Miler and Page, 2009). A study that applies ABM to vehicles and public transport sectors will reflect the technical characteristics of each vehicle type as well as the interactions that reflect external environments, such as the traffic regulations and geographical environments within the model. Based on ABM, Schindler (2013) showed that the introduction of an unmanned vehicle would improve the stability of all traffic. As such, although the utilization of the ABM is high in the field of walking and transportation, usage is expected to further increase following the development of the GIS (Geographic Information Systems) and big data analysis.

Similarly, although studies of infectious diseases and species differ in their approaches based on their role and biology respectively, they share common concepts such as the "predator and prey" relationship. These similarities enable the development of mathematical algorithms underlying each other. By contrast, the use of ABM is steadily increasing to simulate the diffusion model and observe the results. In general, the spread of infectious diseases is suitable for analysis through ABM as it has nonlinear characteristics and requires consideration of various environmental variables. Moreover, the interaction between actors has a significant effect on epidemics. Recently, ABM has also been applied to research on human diseases (Carpenter and Sattenspiel, 2009).

From a macroeconomic perspective, various studies have been conducted considering the unreasonable choices of foreign economic players. It should also be noted that the need for research on the interactional effects between economic players has steadily been increasing. In particular, the existing economic approach may not be appropriate if external shocks from the financial and real estate markets amplify, causing unexpected results. In fact, the sub-prime mortgage crisis in the United States in 2007 led to a global economic crisis, as problems in the U.S. real estate market spread to the financial markets. However, neither the U.S. government nor economists predicted the process and the outcome very well or in a timely manner.

Since the sub-prime mortgage crisis, there has been lively discussion regarding the limitations of existing economic approaches and there have been increased demands for alternative methods of analysis. A study by Poggio et al. (2001) to evaluate the suitability of ABM for financial markets attempted to compare results from real-world experimenters and the simulation results from hypothetical actors in financial markets. The results of the experiments carried out in accordance with the six experimental scenarios were reproducible, which suggested the possibility of using ABM to address problems that would be difficult to identify through actual experiments. The study also proposed the combination of real and modeled actors as experiment participants in a simulation. For example, Brock, Hommes, and Wagener (2009) used ABM to show that hedging, an investment technique to achieve a stable investment portfolio, can disrupt market stability by inducing excessive investment.

There are many studies using ABM in the real estate market, in which various characteristics relating to urban features are studied, and in which city spatial theories have been developed. In this situation, the ABM provides insight into the spatial characteristics by modeling decision-makers and citizens' choices and behaviors in compression. Geankoplos et al. (2011) analyzed that individual real-estate investors tend to use an investment approach that increases leverage based on past investment experience as well as optimistic expectations of rising housing prices. Brown and Robinson (2006) studied changes in urban reckless development caused by changes in the criteria for choosing real estate for housing. They modelled preference behavior by the type of actor, based on actual Detroit area studies, to increase the precision of analysis. Based on this, a simulation analysis was conducted under random conditions. In addition, virtual space was constructed to identify changes in urban development patterns according to the actor's preference, providing useful insights to policymakers. In financial and real estate markets, individual or group decision-making behaviors can ultimately affect the market. In these research fields, the ABM will be more often used along with existing analysis methods because of the high levels of interaction between actors during the decision-making process.

Ⅳ. The ABM Application in the Online Game Industry

Analysis of the effectiveness of government regulation is essential in the online game industry, as government regulation has a profound effect on the industry (Kang et al., 2009). In this chapter, we outline the possibility of online game regulatory effectiveness analysis using the ABM with a pilot case and present additional challenges in implementing a framework that realizes this regulatory effectiveness analysis.

Empirical studies on Korean web board games are limited, and a modeling effort with a simulation is rare (Yoo and Jeon, 2014). Existing studies may be grouped into skepticism, separatism, the regulation-based approach, and macro effects analysis (Jang et al., 2017). First, the skeptic view is that online gaming users may show pathological symptoms because of obsessive Internet access and anonymity (Griffiths, 1999). Second, from a separatist perspective, a rather abstract argument that the Internet is dangerous needs to be verified. For example, a study tracking 18 months of actual user data shows mixed results of adaptive and pathological users (La Plante et al., 2008). Third, a regulatory-based approach holds the view that it should be weighed to determine whether institutional or self-imposed control is more appropriate (Gainsbury et al., 2015). Fourth, the macro-regulatory effect analysis approach uses total volume-based time series analysis (Jang et al., 2017; Yoo and Jeon, 2014).

4.1. Model Design

Libraries for ABM, such as NetLogo, Cougar, Repast, and other independent programs design programs, vary depending on the nature of the study. This pilot study designs ABM using MESA, an ABM library based on Python. The high compatibility with this Python-based data processing library provides the advantages of a more flexible simulation design as it facilitates the extraction and utilization of data needed for analysis and enables intuitive programming. We designed agent behavior to show random patterns over time. RandomActivation, a class in MESA, is prepared to implement this process well. Data generated from the simulations is also collected by the DataCollector MESA class as shown in <Figure 2>. MESA seems to be appropriate to model social science

```
from mesa.visualization.ModularVisualization import ModularServer
from mesa.visualization.modules import CanvasGrid, ChartModule, TextElement
from mesa.visualization.TextVisualization import (
    TextData, TextGrid, TextVisualization
)

from model import SchellingModel


class SchellingTextVisualization(TextVisualization):
    '''
    ASCII visualization for schelling model
    '''

    def __init__(self, model):
        '''
        Create new Schelling ASCII visualization.
        '''
        self.model = model

        grid_viz = TextGrid(self.model.grid, self.ascii_agent)
        happy_viz = TextData(self.model, 'happy')
        self.elements = [grid_viz, happy_viz]

          ⋮          ⋮          ⋮          ⋮
```

<Figure 2> MESA, a Python Framework for ABM (e.g., Schelling Model)

phenomena in that the architecture is simpler and more intuitive than that of its competitors.

All data inputs or outputs from the simulation model were processed using Microsoft's Excel spreadsheet. We utilized Pandas, a data manipulation library for Python, to exchange data between Excel and MESA. We obtained random numbers needed for simulations using Numpy's random number generator. Like statistical programming languages such as R, Python is desirable for data science studies because it has the necessary tools to use data frames by Numpy and Pandas. The Matplotlib package was also used to visually verify the results and we designed classes assuming multi-core environments.

4.2. Parameters

It is crucial to determine the value of attributes for actors and environments using an ABM. The values should adequately reflect reality. We conducted a survey to determine values based on data from actual users. The results of parameter settings that reflect data about game users are summarized in <Table 1>.

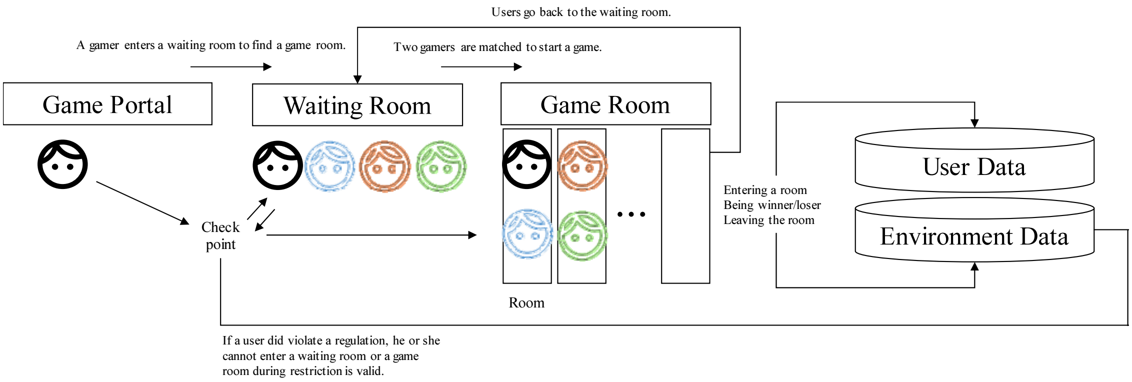
In the web board game context, we did not assume any behavior patterns as default settings. That is, each actor is in a completely random state at the beginning of the simulation. RandomActivation provides the appropriate ability to describe such situations. The results of user's actions were con-

<Table 1> A Sample Table

Parameter	Explanation
Marketing_effect	Probability of attracting users to a game
Payment_customer	Ratio of paying users
Gold_threshold	The minimum required payment (cyber credit) for participating in a game round
Money_gold_conversion_rate	The exchange rate between cash and cyber credit
First_lockdown_rule	The regulation for monthly payment ceiling
Second_lockdown_rule	The regulation for daily payment ceiling
Game_prob	The probability of entering a game room as usual
Game_attraction	A personal propensity toward a game
Gold_join	The initial free game credits for joining
Refresh_month	The monthly renewed game credit
Refresh_month_discount_lower	The monthly refreshment discount (minimum)
Refresh_month_discount_higher	The monthly refreshment discount (maximum)
Addiction_judge	Overindulgence threshold
Max_game_affordable	The maximum amount of disposable income for games
Escape_effort	The chance to quit a game forever
Addiction_effect_min	The chance of overindulgence (minimum)
Addiction_effect_max	The chance of overindulgence (maximum)
Addiction_cure_min	The chance of recovering from overindulgence (minimum)
Addiction_cure_max	The chance of recovering from overindulgence (maximum)
Max_betting	The maximum betting amount per game
Lockdown_policy	The regulation for 24-hour grounding
Strategy	If true, a user can exchange money with cyber credit through illegal channels
Cheating_propensity	The personal propensity to rely on illegal channels (i.e., cheating)
Cheating_propensity_personal_difference_max	The average of differences between users' propensity to cheat (maximum)
Cheating_learning	The chance of imitating others' cheating behavior

stantly recorded based on the point at which each simulation moment (also known as Tick) was completed. In our model, user behavior was implemented as a GameModel object, and the actions taken by each actor were registered and managed in a schedule object. <Table 2> shows a list of data that the model manages as the simulations are executed.

For simulation purposes, the behavior of game users is assumed to be determined daily and the number of games per day is also statistically determined. We focused on overindulgence in playing a web board game and excessive cash expenditure. In addition, it was assumed that environmental changes caused by regulatory policies affected these behaviors. From the start of the month, the upper limit on the amount of cash available to game users is reset. The number of times a user can play a game per day is also designed to be determined by the amount of cash spent. The game betting amount



<Figure 3> Agent Interaction

<Table 2> Agent Variables

Attribute	Description
Gold	Amount of cyber credits (also known as game money)
Lost_gold_day	Amount of credits lost daily
Money	Amount of real payment monthly
Spending	Total amount of real money paid
Day_in_month	Game experiences monthly
Day_experience	Game experiences daily
Freq_month	Game experiences – frequencies
Freq_sum	Game experiences – cumulative frequencies
Addiction	If true, an overindulging agent
Addiction_effect	Personal propensity to overindulge (base chance)
Lockdown	If true, an agent grounded for 24 hours
Earning_total	Amount of illegal earnings by cheating
Cheating_propensity_person	Personal propensity to cheat
Reserved_gold	Game money carried forward

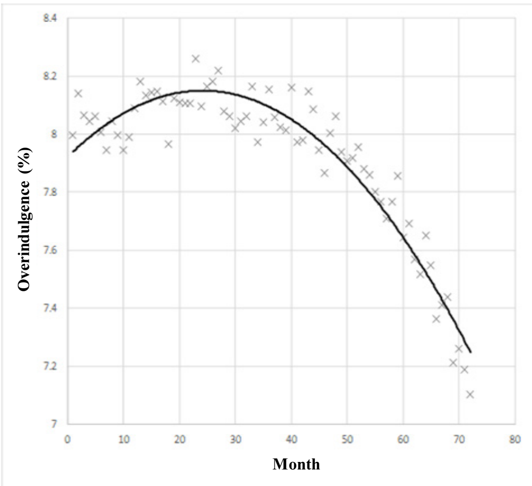
is also set at random; however, the upper limit is restricted to that allowed by government policies in reality.

It should be noted that all player objects are inherited from one generic class, Agent. Game users can enter a game waiting room and enjoy the game according to their preference and how much game money they have. We have introduced the assumption that once they start playing games, users can play repeatedly. In the game, opponents are completely randomized following uniform distributions. Therefore, it is not necessary to identify the opponent. This also faithfully reflects the regulatory reality of the game. In the simulation, each game requires two players like 7 Poker with two opponents. We designed a simpler simulation model by assuming that a winner and other losers were always divided when a game was over. The winner's profits and the losers' losses were zero sum. No additional bonuses were earned through the game.

The state of overindulgence was determined by the number of games played per day on average. The criteria refer to the Korea Creative Content Agency's overindulgence survey in 2017. We posited that the overindulgence state could be improved naturally or by external factors including family care and deterrent actions. There is no tolerance for overindulgence, which means users who have overindulged once or more may enter the overindulgence state again and again. We did not consider the additional effects of multiple overindulgence episodes in the simulations.

Ⅴ. Results

<Figure 4> shows the monthly overindulgence rates of game users. According to the results, if users continue playing a game that was released on the market for more than 70 months, the maximum overindulgence population ratio will be lowered from



<Figure 4> Ratio of Monthly Overindulgent Population in Simulations

8.14 percent to 7.2 percent. Meanwhile, the rate of overindulgence tends to decrease as the time allowed to play games decreases. Overall, the indulgence tendency of a game player shows an increasing pattern in the early days of the game market; however, it has been reduced through the inflection point and appears to be entering a stabilization stage quickly. In addition, we can observe that the less time available to play a game, the lower the risk of overindulgence. Consequently, the most important factor in controlling the rate of overindulgence is how much time a user spent on a game.

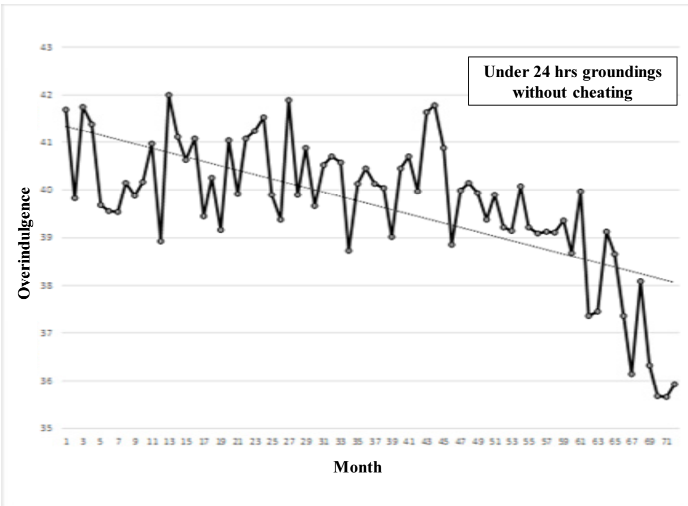
Compared with actual data, the results of the ABM simulation are verified. The results of Korea Creative Content Agency's overindulgence survey in 2017 show that most game users have a play time of less than an hour. By contrast, if a user plays game for more than four hours, the ratio of overindulgence will jump to 22.3 percent. The ABM simulator in this study reflects this reality well, which means there is a significant correlation between game time and overindulgence.

Meanwhile, in the early days of the game, the rate of overindulgence steadily increased, and the trajectory path gradually went through an inflection point. It seems that overindulgent users of the game will remain at a high level for some time. However, if other conditions do not change, the level of overindulgence is greatly reduced at a given time. It is believed that the normal massive multi-user online role-playing games, also known as MMORPG, will be able to maintain the high level of initial overindulgence pattern level by refreshing game settings including posing more quests or releasing new items. However, it should be noted that it is actually very difficult to modify the rules in traditional web board games because those rules identify the game. A web board game needs to be based on well-formed strategies with a precondition that stable rules are guaranteed over a long period of time. Items can be provided in games for free, but this kind of game policies should keep fairness. In this regard, the level of overindulgence of online web board games is likely to undergo considerable adjustment since their launch. In this sense, we should pay careful attention to the timing of the measurement of the level of overindulgence. When negative evidence of some overindulgence in the early days of the game is found, measuring the level of overindulgence can lead to somewhat exaggerated conclusions. By contrast, if observations are collected too late, damage caused by overindulgence can be underestimated.

What is the background for such a result? Step-by-step tracking on the simulation status shows that users' disposal money is associated with the number of game plays per day. In reality, most users are free users, and our simulations are based on user surveys as the same. After losing the bonus money for signing into a game, game players reduce their actual playing time based on the amount of betting money they have. If a user wants to play again, he or she must wait for free refill, which leads to a lower risk of overindulgence. In the real world, the game company provides free random items to keep users playing a game.

So, what would happen if some users had a very large overindulgence propensity? The results of the simulations show that overindulgence may continue for a considerable period. As a result, the tendency to overindulge is in control, but the damage over the period is expected to be significant. <Figure 5> shows the simulation result when the user's involvement in the game is significantly greater (addiction effect = 0.4). The linear trend line shows that the width of the change continues in the direction of reduction (slope = -0.05, R^2 = 44%). The rate of change of overindulgence will change from a minimum of 38.6 percent for three years (36 months) to a maximum of 42.1 percent after six years.

The question we were asking was: "Will policy efforts help avoid overindulgence?" The results of the simulations clarify two facts. First, overindulgence depends on the total amount of game money available to game users. This means that controlling disposable



<Figure 5> Overindulgent Population Under 24 Hours Grounding Regulation

income in the game can have a significant effect on the level of overburden.

We set the total amount of monthly and daily disposable cash and the limit of cash that can be lost daily in our simulations. The effect of the first condition seems to be cumulative. The game user is not able to recover from normal conditions until the next month if he or she loses everything, which means game participation is impossible because of the lack of disposable money. During this period, the users' overindulgence propensity is constantly reduced.

Furthermore, the total amount of daily disposable game money is associated with a total betting amount per trial. As the amount of money that can be bet approaches the regulation ceiling, the effect of reducing the time that a game can be played in one day is observed. Paradoxically, if a person is not overindulging, letting him or her bet more may help reduce the danger of overindulgence.

Finally, we summarize the effects of the regulation that would force a user to stop if he or she lost a significant amount of money in a game. While the two previous regulations have monthly and daily controls, they concern what happens when a user plays a game. If a regulation is placed on Y when the amount bet is X, the regulation is useless when X is less than Y. However, the regulation does alert the user not to bet until Y.

Ⅵ. Conclusions

Interaction between players in online games becomes an important game feature for fun (Um and Kim, 2006). Competition in online game is essential in increasing commitment of users due to psychological consequences from winning and losing (Hsu et al., 2009). Studies on online game features have focused on why game players spend time and efforts in virtual worlds (e.g., Choi, 2007; Hsu et al., 2009; Lin and Sun, 2011); however, the research stream of game industry did not pay much attention to the other side of competition in online web board game. It should be noted that an enthusiastic game user must pay real money to buy virtual items for more betting in a game room. More commitment he or she has, more cash will be spent (Lin and Sun, 2011). The problem is that winning and losing yields to transferring wealth like traditional gaming. Although virtual cash (or items) cannot be refunded by rights, users can fabricate fake losing to get real cash (Choi, 2007). Game developers should pay much attention to the possibility of illegal money trading in a game. The lack of countermeasures to illegal money trading with virtual items in online web board games makes people perceived the game just like a kind of online casino.

The results of our simulations firstly show that game users have not maintained a particular level of overindulgence. In other words, different conclusions can be drawn on the performance of regulations depending on when the effectiveness was measured. Korean authorities have not publicly commented on the agreed methods for measuring regulatory effectiveness. Similarly, game developers have never released data to the public for scientific evidence against overindulgence. Efforts to overcome this situation and secure a more scientific and rational basis may contribute to keeping the game industry and public health.

In this sense, the simulator in this study requires constant improvements. First, the data should reflect reality more comprehensively to introduce a dynamic model, which is more suitable for understanding the effects of regulation in time-varying situations. In addition, tracking how the propensity to overindulge changes longitudinally can help adjust the agent and environment variables in the simulation to make them more realistic. Moreover, it should be significantly noted that we assumed randomized uniform distribution as a basis of stochastic user behavior in a game. However, there are clearly possibilities on sequential processes which should be reflected properly in a simulator. Data obtained from real world will be helpful in developing probability functions to predict user behavior. For example, a deep learning model with the Long Short-term Memory (LSTM) algorithm can be applied.

Research on online game regulation using ABM is insufficient. One reason is that the online game industry does not produce enough data to be of interest to simulation research communities. However, in recent years, game regulation has emerged as an issue with significant social consequences. By contrast, it is socially and ethically undesirable to introduce an experimental method to understand the effects of game regulation that sacrifices game users' economic benefits. Nevertheless, efforts are needed to quantitatively measure and understand the effect of regulation, as regulation should not hinder the growth of the game industry whereas it should create conditions that are socially desirable.

ABM helps researchers design models based on real world assumptions and data to analyze risky and costly problems. By assuming different scenarios and conducting repeated low-cost analyses, researchers can understand the essential structure behind phenomena in a timely manner. In this study, we have introduced how ABM, which has been used in various research areas, can be applied to analyze cases of online game regulatory effectiveness. This study is the first research case in which the micro-effects of regulation are analyzed using a simulation method.

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