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A Dynamic Model of Rational Addiction and Tedium: An Empirical Examination of an Online Game

합리적 중독과 권태의 구조적 동태 모형: 온라인 게임 소비 행동의 계량적 분석

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서울대학교 대학원
경영학과 경영학전공
김 종 대

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지도 교수 송 인 성

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Abstract

A Dynamic Model of Rational Addiction and Tedium: An Empirical Examination of an Online Game

Jongdae Kim

College of Business Administration

The Graduate School

Seoul National University

We propose a dynamic structural model of rational addiction to elucidate consumer behavior for online game consumption. Particularly, we propose a revised and extended utility model for rational addiction, by introducing the tedium factor based on a two-factor model of addiction. We demonstrate that the proposed model adequately explains consumer behavior in online gaming, particularly in modeling consumption reduction and churn patterns that cannot be explained by the existing rational addiction model. Moreover, we perform counterfactual simulations related to tedium and level-up difficulties, which affect consumption decisions and quantities as expected. Related discussion and implications are also provided.

Keyword: Online game consumption behavior, dynamic structural model, rational addiction, tedium

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1. Introduction

Online games have become a dominant form of entertainment in recent years (Griffiths, Davies, and Chappell, 2003; Xu, Turel, and Yuan, 2012; Nevskaya and Albuquerque, 2019). Accordingly, studies have been conducted to explore consumers' online gaming behavior. Interestingly, most studies related to online games have focused on modeling consumer behavior as addictive, since consumption patterns of online games seem to be excessive, which can easily be explained by the concept of addiction. Specifically, consumers may be addicted and spend a long time playing a game. In this study, we explore consumer behavior to understand whether they are addicted to gaming and, if so, how they are addicted to it.

We follow the research spirit of the rational addiction model suggested by Becker and Murphy (1988), which defines addiction as addictive behavior induced by consumers' utility maximization with forward-looking behavior. They measured unobserved addiction by the past consumption stock, employing the idea of "learning by doing." However, we argue that the existing approach of Becker and Murphy (1988) is not sufficient to model online game consumption patterns such as reduction and exit. Therefore, we proposed the model with a new factor, tedium, based on the psychology literature related to addiction, such as Berlyne (1970), who proposed a two-factor addiction model, which constitutes addiction behavior as the sum of two subfactors, positive learning and negative tedium. Berlyne (1970) argued that when consumers are exposed to a new stimulus, they learn and continue consuming it as positive learning. However, after a certain point of learning, they become tired of being repetitively exposed to a stimulus and want to stop consuming it as negative tedium. We argue that the rational addiction model of Becker and Murphy (1988) is a partial model to consider a positive learning factor alone from the point of view of Berylne (1970). Therefore, we include a tedium factor for explaining online game consumption behavior.

Utilizing the framework of Berylne (1970), we propose a dynamic structural model to capture consumption patterns that existing addiction models cannot explain. We demonstrate that the proposed model can explore not only when and how consumers become addicted to online games, but also when and why consumers are no longer addicted, so that they reduce or even stop gaming consumption. We suggest the estimation and related policy intervention results.

We expect that our research will contribute to the marketing and economics literature in three ways. First, we propose the extended and revised rational addiction model by introducing a tedium factor in the utility model. We expect this approach to be more appropriate for the original research spirit of Becker and Murphy's (1988) approach. Second, the proposed model can provide the empirical framework that can be utilized by the literature following the two-factor addiction model of Berylne (1970). Particularly, the level is established as a notably influencing factor for the tedium accumulation process, so that related studies can employ and extend their research using this new factor in the literature. Third, we expect the results of this study to provide deeper insights into the literature on online game consumption behavior. The results emphasize the importance of tedium in modeling online game consumption behavior, while most prior studies have focused on addiction as learning. We conduct counterfactual policy simulations to show how tedium can affect consumer behavior.

The remainder of this paper is organized as follows. Section 2 discusses related literature on online game consumption behavior, rational addiction, and tedium. Section 3 introduces data and provides the results of the model-free analysis. Section 4 proposes our model and the laws of motion of state variables for dynamic decision problems. Section 5 suggests estimation results, identification strategy, and the results of policy counterfactual simulations. Section 6 concludes with a discussion of the implications, limitations of the present work, and directions for future research.

2. Literature Review

2.1. Online Game Consumption Behavior

Online games are considered a popular form of entertainment (Griffiths, Davies, and Chappell, 2003; Xu, Turel, and Yuan, 2012; Nevskaya and Albuquerque, 2019). Numerous studies have been conducted to explore consumers' online gaming behavior, such as motivations for playing online games. For example, factors such as dissociation, virtual friendship, entertainment, coping with stress, loyalty, empowerment, and immersion can affect online game consumption behavior (Kuss and Griffiths, 2011; Beranuy, Carbonell, and Griffiths, 2013). The antecedents of online gaming behavior were investigated using the functionalist perspective as well. Factors such as the need to master game playing mechanisms, relationships with other users, and escapism from real-life problems were found to increase online gaming, while factors such as attention switching activities, perceived cost, and education related to the potential side effects of the excessive activity were found to reduce online game consumption (Xu, Turel, and Yuan, 2012).

However, most related studies have focused on excessive gaming or possible addiction to online games. They are crucial to study because they can negatively influence the personal, social, and financial aspects of our lives (Kuss and Griffiths, 2011; Xu, Turel and Yuan, 2012; Nevskaya and Albuquerque, 2019). Several studies have particularly focused on the influencing risk factors of online game addiction. Personality traits (e.g., loneliness, introversion, aggression, low self-esteem), motivations for playing games (e.g., coping with negative emotions, escapism, virtual relationship, entertainment, reward), and structural characteristics of games (e.g., genre, virtual character) have been discussed in the literature (Kuss and Griffiths, 2011). Mehroof and Griffiths (2010) argued that personality traits such as neuroticism, anxiety, and aggression are associated with online game addiction. Xu, Turel, and Yuan (2012) also investigated the influencing factors on online game addiction. They found that the need for a relationship and escapism from real life can increase online game addiction, while attention switching activities and parental monitoring can reduce it.

In the context of product usage management, Nevskaya and Albuquerque (2019) proposed a structural model to control the excessive use of online products such as online games. They demonstrated that we can obtain a beneficial outcome for both consumers and the firm by redesigning reward schedules and usage time limits, which can result in higher revenues and lesser time devoted to online games. They argued that this result is considering that slower game consumption leads to an increase in long-term product engagement.

2.2. Rational Addiction Model

We follow the rational addiction model proposed by Becker and Murphy (1988) to model addiction behavior in an econometric fashion. They argued that people can become addicted not only to gaming, cigarettes, and alcohol, but to many other things such as work, religion, music, films, friends, and lovers. Effectively, addictive behavior is not always limited to negatively cognitive products, but can be related to more general activities in our lives. In the literature, addiction is defined as: “Someone is addicted to a good when past consumption of the good raises the marginal utility of present consumption.” (Becker and Murphy, 1988) This concept is closely related to adjacent complementarity and reinforcement. They also defined rational addiction in that consumers make their decisions by utility maximization with forward-looking behavior. Rational addiction is defined as “Addictions are usually rational in the sense of involving forward-looking maximization with stable preferences.” (Becker and Murphy, 1988) We expect gaming users in general to perform the rational decision-making process. Notably, gaming users even in the high addiction level can conduct the distorted-rationality process described by Turel, Serenko, and Giles (2011). Since addiction or rational addiction is hardly directly observed in real data, we require alternative ways to measure addiction stock. Becker and Murphy (1988) suggested the measurement by employing the idea of learning by doing. Consumers can learn how attractive a product or a brand is through learning, and this information can be measured by past consumption patterns. Based on this, we can measure addiction as a summary of past consumption history or consumption capital.

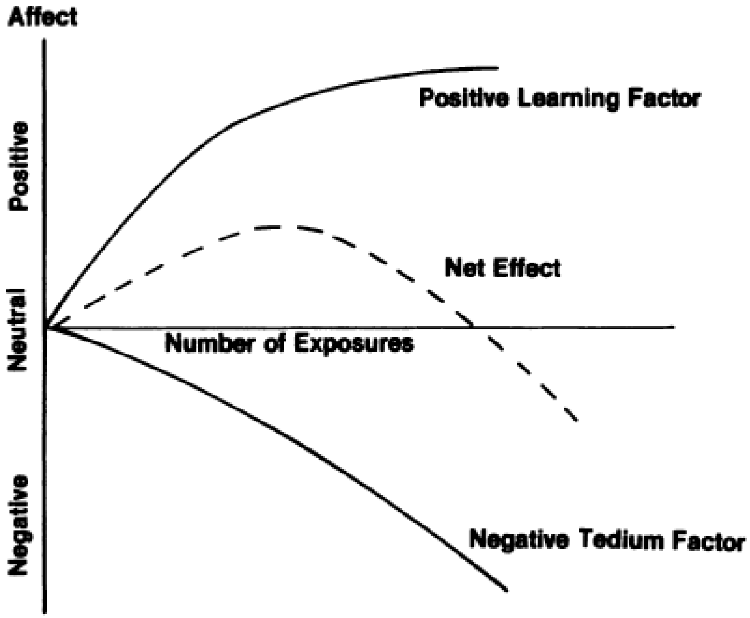
The approach of rational addiction has been vigorously utilized in the marketing and business literature. Gordon and Sun (2015) proposed a dynamic structural model of rational addiction with consumption and stockpiling to study consumers' tendencies to respond to new policies that aim to curtail cigarette purchase. They showed that the category demand elasticity is lower when ignoring addiction and that purchase and consumption elasticity in the short term can be varied from purchase elasticity using a series of simulation studies with temporary and permanent price cuts. Chen and Rao (2020) proposed a dynamic structural model of rational addiction to incorporate purchase and consumption of e-cigarettes as well as cigarettes. They evaluated the effect of the current policies and conducted potential policy interventions on e-cigarettes. Both studies proposed a rational addiction model based on dynamic programming with the utility model and addiction measurement suggested by Becker and Murphy (1988). For reduced-form (non-structural) models, Becker et al. (2017) showed empirical evidence of addictive behavior using cigarette purchase data, and Kwon et al. (2016) demonstrated the existence of addictive behavior in mobile social applications usage.

2.3. Tedium

In the psychology literature, limited studies have explored the influencing factors on addiction behavior. Berlyne (1970) suggested a two-factor addiction model. They argued that when consumers are exposed to a newer stimulus, they learn what it is and continue consuming it as a positive learning factor, while they can become tired of being exposed to the stimulus at a certain point and may want to stop consuming it as a negative tedium factor. These two factors constitute their two-factor addiction model, and the net effect of addiction follows the inverted-U curve, as presented in Figure 1. We argue that the Becker and Murphy (1988) approach is a partial model considering only the positive learning factor from the point of view of Berylne (1970). Therefore, we extend the existing rational addiction model by utilizing a tedium factor.

Tedium can be influenced by two sub-factors. One is repeated exposure to the same stimulus. A positive learning factor in addiction occurs when consumers can learn something new. However, after exposure to the same stimulus sufficiently many times, anything new to be learned may no longer remain (i.e., saturation of learning). Thereafter, a tedium factor arises and can be accumulated. The other sub-factor is complexity. The complexity of the way you consume and use can depreciate a tedium stock or delay the starting point of boredom (Berylne, 1970).

[Figure 1] A Two-factor Model of Addiction



Source: Rethans et al. (1986)

A two-factor addiction model has been widely utilized in the marketing and business literature, especially modeling for brand choices and repetition effects in advertising. In the brand choice model literature, Bawa (1990) adopted this approach to explain inertia and variety-seeking behavior. They argued that inertia behavior in brand choice is similar to addictive behavior (e.g., reinforcement) and variety-seeking behavior is analogous to tedious behavior, which comes into play when consumers become bored with the same product over time. They demonstrated that inertia and variety-seeking behavior may coexist within the individual at different times, and identified the existence of a mixture of inertia and variety-seeking choice behavior. Prior studies also adopted a two-factor addiction model to investigate repetition effects of advertising. A study by Rethans et al. (1986), one of the first utilizing a two-factor addiction model in the marketing literature, proposed the model of message repetition effects in new product advertising and tested hypotheses based on the two-factor model. They conceptualized and measured tedium as increasingly negative feelings and reactions toward experiencing the same repetitive stimuli. They argued that tedium can be accumulated when the frequency of repetitive exposure increases, which indicates that the measurement of tedium in the present research can be justified in the literature. Campbell and Keller (2003) demonstrated that brand familiarity can influence consumers' habituation and tedium. When consumers are repeatedly exposed to an advertisement of an unfamiliar brand, they may learn about the brand a few times. Once they have been exposed to the same ad many times, they can experience tedium because there is very little left to learn. Prior studies such as Cox and Cox (1988) and Anand and Sternthal (1990) extended the two-factor addiction model by considering the complexity, which is an ease of message processing in advertisements. They showed that stimulus complexity can enhance the relationship between exposure and preference. This result can be explained by several studies, which argued that the preference for the complex stimulus tended to enhance with repeated exposures, while the preference for the simple stimulus tended to decrease (Berlyne, 1970; Saegert and Jellison, 1970; Stang and O'Connell, 1974; Smith and Dorfman, 1975). Cox and Cox (2002) extended this approach to new product designs. They found that consumers' preference for complex designs tended to increase with repetitive exposures, whereas liking for simple designs was prone to decrease. Pieters, Wedel, and Batra (2010) extracted visual features from advertisements and explored their roles in attention and attitude toward the ads. They defined the complexity based on color, luminance, and edges as feature complexity, which is related to data variation at the individual pixel level, and defined the complexity in terms of shapes, objects, and patterns as design complexity, which is connected to more elaborate and creative designs. Van Grinsven and Das (2016) explored the effects of brand logo design complexity and exposure in advertising. They found that increases in exposure led to improved brand recognition and attitudes, particularly for complex brand logos, and they argued that this is because logo design complexity moderates the effect by delaying tedium accumulation. Maier (2019) proposed the model of serial product evaluations online and found that image complexity can delay a wear-out period caused by tedium.

3. Data and Model-free Analysis

3.1. Data

We utilize a dataset for the game consumption history to explore consumption patterns. Specifically, we use the *World of Warcraft* avatar history dataset offered by Lee et al. (2011, February). *World of Warcraft* is a well-known online video game, one of the most popular products of a massively multiplayer online role-playing game genre (i.e., MMORPGs), developed by Blizzard Entertainment. Lee et al. (2011, February) collected the rich user-level log data by using a function of the trace at regular intervals (i.e., every ten minutes) in a specific *World of Warcraft* realm (i.e., the Light's Hope realm in Taiwan). For over 1,107 days between January 2006 and January 2009, they collected data for 91,065 avatars and 667,032 sessions. This dataset includes specifics such as query time, avatar ID, and the current level information. The descriptive statistics are presented in Table 1.

3.2. Model-free Analysis

In this section, we investigate the empirical evidence on addictive and tedious consumption behaviors. First, we suggest examples of the consumption history that the existing rational addiction model approach may not sufficiently explain. Particularly, we present graphic examples of consumers who reduce or stop their consumption even if they may have accumulated addiction. Figure 2 suggests descriptive evidence to justify the proposed model by including a tedium factor. Panel A of Figure 2 shows repetitive consumption patterns of the inverted-U curve, implying that some consumers reduce their consumption even when they may have some extent of addiction stock, and after some period, they are back to playing a game. Panel B of Figure 2 shows an example of a churn from consumption after highly addictive consumption behavior, indicating that some consumers reduce and stop their consumption even with a substantial extent of addiction stock.

Next, we suggest model-free evidence of addictive and tedious consumption behavior, respectively. Following the rational addiction literature, we assume that past consumption quantities increase the current consumption quantities if consumers are addicted to consumption. Therefore, we expect a positive correlation between past consumption stock and current consumption quantities. In addition, we expect that repetitive exposure to the same stimulus reduces consumption if consumers find it tedious.

[Table 1] Descriptive Statistics

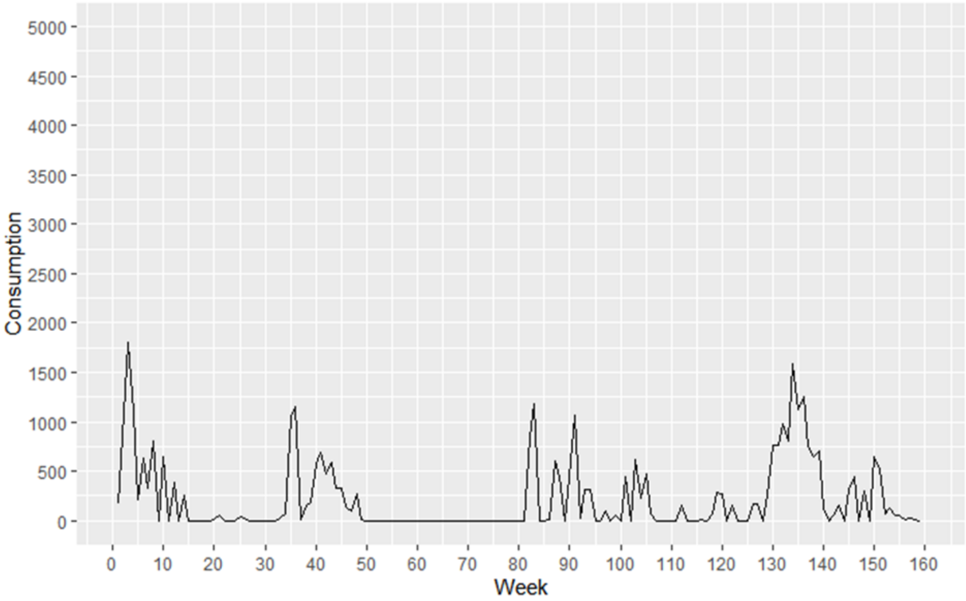
Min	Median	Mean	Max	Standard Deviation
10.0	170.0	574.5	10040.0	909.7

10%	20%	30%	40%	50%	60%	70%	80%	90%
10	20	40	90	170	310	550	970	1,740

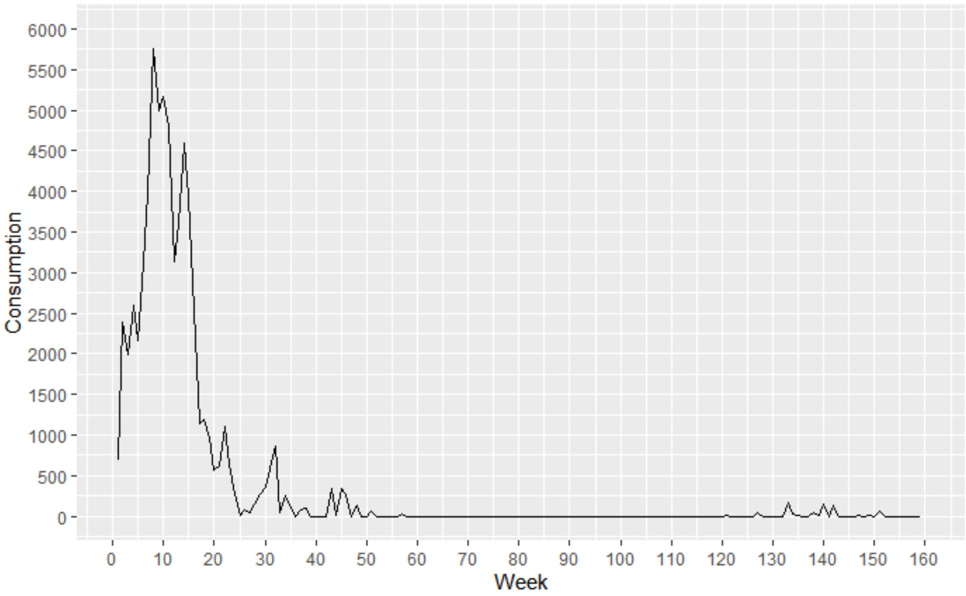
Notes. This table is calculated with week-level time playing a game when users consume an online game (i.e., we calculate this table after non-consumption (c=0) points) because the data is very sparse. And this table is for users who played a game more than one week (n=40,901).

[Figure 2] Evidence of Tedious Behavior

Panel A: Consumption Reduction



Panel B: Consumption Churn



Accordingly, we expect a negative correlation between cumulative consumption at the same level and current consumption quantities. These assumptions also provide the base of our identification strategy for addiction and tedium stock, which is discussed in Section 5.2.

To justify these assumptions, we perform fixed effects models by measuring proxies for addiction and tedium stock. A proxied addiction stock is measured by the cumulative consumption stock that contains information about learning the elements in an online game. A proxied tedium stock is measured by the cumulative consumption stock at the same level, which is regarded as the same stimulus in this study. By utilizing these proxies as explanatory variables, we perform three models: Model 1 is to solely use a proxied addiction stock; Model 2 is to solely use a proxied tedium stock; Model 3 is a full model that uses the two proxied stocks.

The results of the fixed effects models for the empirical model-free evidence are summarized in Table 2. All the results are as expected. For all models, the proxied addiction stock has a positive effect on current consumption, and the proxied tedium stock has a negative effect on current consumption.

[Table 2] Model-free Analysis Results: Results of the Fixed Effects Model

	Dependent Variable: C_{it}
Model 1	
$\log(C_{it}+1)$	0.6319 (0.0003) ***
$\log(\tilde{A}_{it}+1)$	0.0193 (0.0002) ***
Model 2	
$\log(C_{it}+1)$	0.6499 (0.0003) ***
$\log(\widetilde{N}_{it}+1)$	-0.0411 (0.0002) ***
Model 3	
$\log(C_{it}+1)$	0.5684 (0.0003) ***
$\log(\tilde{A}_{it}+1)$	0.2801 (0.0004) ***
$\log(\widetilde{N}_{it}+1)$	-0.3170 (0.0004) ***

Notes. *** p<0.001 ** p<0.01 * p<0.05

4. Model

In this section, we propose the utility model that includes a new factor, tedium. Notably, we revise and extend the utility model rather than merely following the rational addiction approach of Becker and Murphy (1988). We employ the dynamic structural model to explore online game consumption from the perspective of the rational addiction model. A dynamic structural model is developed based on the Markov decision process in which a decision-maker in the current state takes an action that settles current utility. Those affect the distribution of the state in the next period through a form of the Markov transition probability. By utilizing the value function optimization and bellman equation, we can redesign a complex stochastic optimization problem as a sequence of simpler deterministic optimization problems. It is appropriate in the sense that the dynamic structural model is to model the sequential and forward-looking decision-making process under uncertainty, which is closely related to the definition of rational addiction. We expect that we can explain the decision-making process or mechanism for consumption patterns for online games, and explore the relationships of variables that are difficult to determine when using reduced-form models. Here, we can estimate the effect of unobservable states such as addiction and tedium.

Furthermore, we can obtain policy invariant estimates and perform policy intervention simulation studies to investigate the impact of new policies.

To propose the structural model, we need to define the utility model, decision (action) variable, and state variables with their law of motions. We use online game consumption (C_{it}) as a decision variable. We model it as a discrete choice model by dividing consumption into a few sections. In the remainder of this section, we propose the utility model and the laws of motion for state variables, addiction, tedium, and level.

4.1. Utility Model

Prior literature, such as Gordon and Sun (2015) and Chen and Rao (2020), follows the utility model proposed by Becker and Murphy (1988). They assume quadratic utility functions with linear first-order conditions.

$$u(C_{it}, A_{it}; \alpha_i) = \alpha_{i1} C_{it} + \alpha_{i2} C_{it}^2 + \alpha_{i3} A_{it} + \alpha_{i4} A_{it}^2 + \alpha_{i5} A_{it} C_{it} \quad (1)$$

$$\alpha_{i2}, \alpha_{i4} < 0 \; for\ concavity$$

If we follow Becker and Murphy (1988) and additionally include the tedium factor with quadratic functions, we can assume an alternative utility function as follows:

$$u(C_{it}, A_{it}, N_{it}; \alpha) = \alpha_1 C_{it} + \alpha_2 A_{it} + \alpha_3 N_{it} + \alpha_4 C_{it}^2 + \alpha_5 A_{it}^2 + \alpha_6 N_{it}^2$$
$$+\alpha_7 C_{it} A_{it} + \alpha_8 C_{it} N_{it} + \alpha_9 N_{it} A_{it} \qquad (2)$$

Instead of recklessly following the approach of Becker and Murphy (1988), we revise and extend the existing utility model. We argue that the existing utility model is not appropriate for the fundamental modeling purpose since it cannot properly explain the mechanism of decreases in consumption. By definition, addiction can explain the mechanism of increases in consumption by a positive correlation between past consumption history and current consumption. However, consumption reduction cannot be explained by this definition of addiction. We argue that considering tedium in the model can overcome this problem. From the policy implication perspective, the proposed model including tedium instead of the quadratic term of addiction provides valuable alternatives to control consumption reduction induced by tedium. We perform the counterfactual simulation and discuss the results in

Section 5.3.

Moreover, for the existing utility model in the literature, the main (A_{it}) and quadratic terms (A_{it}^2) of addiction do not seem to have economic meanings to interpret. For example, addiction can be measured as the consumption stock, but it cannot be discussed in the same way as other types of stock or assets (e.g., wealth). We argue that the positive estimate of the main effect of addiction (α_2) does not have substantial meaning and should not be discussed as having a positive effect on utility. The effect of the three-way interaction term (α_9) is also challenging to find a clear implication. Note that we can obtain a more parsimonious model if we exclude nuisance variables that do not have economic meanings. The existing utility model may fit the data of consumption reduction by the quadratic term of addiction. However, we argue that this approach without economic meanings does not fulfill the spirit of the rational addiction model. Therefore, the proposed utility model in the present research with state variables $S_{it} = \{A_{it}, N_{it}\}$ and the parameter vector $\alpha = \{\alpha_1, \alpha_2, \alpha_3, \alpha_4\}$ is as follows:

$$u(C_{it}, S_{it}; \alpha) = \alpha_1 C_{it} + \alpha_2 C_{it}^2 + \alpha_3 C_{it} A_{it} + \alpha_4 C_{it} N_{it} \tag{3}$$

where $0 \leq C_{it} \leq 10{,}080$ (i.e. the maximum value of a week in minute unit), $0 \leq A_{it}$, $0 \leq N_{it}$, and α_2 is assumed as a negative value. In this model specification, if $\alpha_3 > 0$, it captures the reinforcement effect induced by addiction, and if $\alpha_4 < 0$, it captures the decreasing effect of tedium on the marginal utility of consumption.

The forward simulation study finds that this model is sufficient for modeling consumption patterns for addictive and tedium behaviors. Therefore, we decide to revise and extend the rational addiction model in this manner.

4.2. The Law of Motion

4.2.1. Addiction (A_{it})

To measure the unobserved addiction stock, we utilize the standard law of motion in the literature. As Becker and Murphy (1988) suggested, we use the idea that past consumption history affects addictive behavior through the process of learning as follows.

$$A_{i,t+1} = (1 - \delta_A)A_{it} + C_{it}, \ \ 0 \leq \delta_A \leq 1, \quad A_{i1} = A_{i0} \tag{4}$$

An addiction stock evolves deterministically depending on a depreciation parameter (δ_A) and an initial value of addiction (A_{i0}). We assume $\delta_A = 0.5$ following prior literature.

4.2.2. Level (L_{it})

Following prior literature, we use two sub-factors to drive tedium. The first sub-factor is how different the stimulus is, and we expect that it is driven by whether level-up happens. The amount of tedium will increase if a user plays a game in the same environment for many sequences. A new stimulus given by level-up can bring marginally or largely different stimulus to users. For example, users at a higher level can use newer items or skills that have not been used before, and may deal with more challenging quests as new stimuli. Therefore, we use information about whether a user's level goes up or not to model the tedium accumulation process. Specifically, we will model it in that level-up depreciates a tedium stock, while failure to level up does not have an effect on tedium stock. The second sub-factor to drive tedium is the extent of the current level. We expect that the higher the current level, the harder it is to level up, because the difficulty of level-up is more challenging at a higher level. In the data, we find that the level-up probability is smaller when the current level is higher. If the difficulty of level-up is more demanding, a user has to spend more time playing a game in the same environment, indicating that tedium might be more easily accumulated at a higher level. Accordingly, we use the current level to model tedium in that the speed of accumulating tedium is influenced by the level extent. In short, we use the level-up and current level information in data to propose the law of motion for the unobserved tedium stock. Note that level is included in the state space but not in the utility model specification.

The law of motion for level is as follows:

$$L_{i,t+1} = \begin{cases} L_{it} & if\ C_{it} = 0 \\ L_{it} + l, \quad l = 0, \dots, 80 - L_{it} & if\ C_{it} > 0 \end{cases} \tag{5}$$

The level state evolves probabilistically conditional on the increment of level. In this study, we assume that for each L_{it}, the probability distribution of $L_{i,t+1}$ follows an exponential distribution. The exponential specification in the continuous case is approximated with an 80−(L_{it}−1)-point probability distribution in the discrete case (including the not-to-level-up case), by using a simple continuity correction.

For each level, the probability of level in the next period is as follows. Each mass point is calculated as the probability of an exponential random variable coming within plus or minus 0.5 of the assigned integer values.

- For $1 \leq L_{it} \leq 78$

$$\Pr\left(L_{i,t+1} = L_{it} + l \mid L_{it},\, \lambda_l\right)$$

$$= \begin{cases} \int_{0}^{0.5} \lambda_l \exp\{-\lambda_l y\}\, dy, & l = 0 \\ \int_{l-0.5}^{l+0.5} \lambda_l \exp\{-\lambda_l y\}\, dy, & l = 1, \dots, 80 - L_{it} - 1 \\ \int_{l-0.5}^{\infty} \lambda_l \exp\{-\lambda_l y\}\, dy, & l = 80 - L_{it} \end{cases}$$

…… (6-1)

- For $L_{it} = 79$,

$$\Pr\left(L_{i,t+1} = L_{it} + l \mid L_{it},\ \lambda_l\right)$$

$$= \begin{cases} \displaystyle\int_0^{0.5} \lambda_l \exp\{-\lambda_l y\}\, dy, & l = 0 \\ \displaystyle\int_{l-0.5}^{\infty} \lambda_l \exp\{-\lambda_l y\}\, dy, & l = 1 \end{cases}$$

…… (6-2)

- For $L_{it} = 80$,

$$\Pr\left(L_{i,t+1} = L_{it} \mid L_{it},\ \lambda_l\right) = 1$$

…… (6-3)

We assume that the parameter of the exponential distribution, λ_l, is influenced by the current level extent and current consumption quantity. It can suitably be estimated outside dynamic programming. When l follows exponential distribution with λ_l, we estimate λ_l as follows:

$$\lambda_l = g(L_t, C_t) = \alpha_0 + \alpha_1 L_t + \alpha_2 C_t \tag{7}$$

Finally, the probability of level up ($h_{it} = 1$), which is used in the law of motion for tedium, is as follows:

$$\Pr(h_{it} = 0) = \Pr\left(L_{i,t+1} = L_{it}\right)$$

$$\Pr(h_{it} = 1) = \Pr\left(L_{i,t+1} > L_{it}\right), \text{ which is smaller at the higher level.} \qquad (8)$$

4.2.3. Tedium (N_{it})

Based on the aforementioned level state model, we propose the law of motion for the tedium state. If the level increases ($h_{it} = 1$), the tedium stock will decrease in the next period by a depreciation parameter (δ_N). On the contrary, if the level does not increase, the tedium stock will not depreciate and accumulate by the current consumption. Note that the level cannot decrease in this model specification. We can regard this law of motion as the step function depending on the level-up information. The law of motion specification is as follows:

$$N_{i,t+1} = (1 - \delta_N h_{it})(N_{it} + C_{it}),\ \ 0 \leq \delta_N \leq 1,\ \ N_{i1} = N_{i0}$$

$$= \begin{cases} (1 - \delta_N)(N_{it} + C_{it}) & level\ up\ (h_{it} = 1) \\ N_{it} + C_{it} & not\ to\ level\ up\ (h_{it} = 0) \end{cases} \tag{9}$$

The tedium factor in the next period, N_{it}, evolves probabilistically based on the probability of level up (h_{it}). Since the level-up probability is more negligible at the higher level extent, N_{it} will be more accumulated at the higher level, as we assumed. It also evolves depending on a depreciation parameter (δ_N) and an initial value of addiction (N_{i0}). We assume $\delta_N = 0.7$, which is larger than $\delta_A\ (= 0.7)$ because we assume that tedium will be more easily depreciated than addiction.

4.2.4. State Evolution

In Table 3, we summarize the definitions and process of state evolution. At the beginning of period *t*, addiction (A_{it}) and tedium (N_{it}) are measured, and a user makes a decision for optimal consumption (C_{it}). Subsequently, the final level extent (L_{it}) is set, and the level up dummy (h_{it}) is settled. Based on this information, addiction ($A_{i,t+1}$) and tedium ($N_{i,t+1}$) for the next period *t+1* are

[Table 3] Summary of State Evolution

	Variable	Criterion
C_{it}	Consumption (Decision variable)	During period t
$A_{i,t+1}$	Addiction stock (State variable; unobserved in data)	At the beginning of period t+1
$N_{i,t+1}$	Tedium Stock (State variable; unobserved in data)	At the beginning of period t+1
L_{it}	Level (observed in data)	At the end of period t
h_{it}	Whether level up or not (observed in data)	At the end of period t

measured at the beginning of $t+1$. A user makes a consumption decision again, and the process goes on.

4.3. Dynamic Decision Problem

A decision-maker solves an infinite time horizon optimization problem in the dynamic programming framework and makes her optimal consumption choice C_{it}^{*}, given their current state and utility. Assuming that the discount factor is known as $\beta = 0.95$, the Bellman equation is defined as:

$$\mathrm{V}(S_{it}) = \max_{C_{it}}\{u(C_{it}, S_{it}; \alpha) + \beta\mathrm{E}[\mathrm{V}(S_{i,t+1})|S_{i,t+1}]\} \tag{10}$$

$$\text{s.t. } 0 \leq C_{it} \leq 10{,}080$$

We perform the value function iteration to solve the value functions and determine the optimal consumption C_{it}^{*}.

$$C_{it}^{*} = arg \max_{C_{it}}\{u(C_{it}, S_{it}; \alpha) + \beta\mathrm{E}[\mathrm{V}(S_{i,t+1})|S_{i,t+1}]\} \tag{11}$$

$$\text{s.t. } 0 \leq C_{it} \leq 10{,}080$$

In this study, we estimate the discrete choice model using maximum likelihood. Let D_{it} be the consumption decision of consumer *i*. This value is assigned as one of the decision values d_{itq}, which is based on the discretization of consumption quantities. With optimal consumption C_{it}^{*}, the consumption decision $D_{it} = d_{itq}$ as a discrete choice is assigned. The discrete choice probability that consumer *i* chooses d_{itq} at time *t*, given the extreme value distribution of the error term, is as follows:

$$\Pr\left(D_{it} = d_{itq} | S_{it}; \alpha\right) = \frac{V_{itq}(S_{it};\alpha)}{\sum_{q'} \exp(V_{itq'}(S_{it};\alpha))} \tag{12}$$

where $V_{itq}(S_{it}; \alpha)$ is the value function for the consumption choice d_{itq}. Finally, the log-likelihood function over all individuals and all periods is used to estimate using the maximum likelihood.

5. Estimation

In this section, we suggest our estimation strategy, including discretization of decision and state variables. Subsequently, we present the results of estimation and policy simulation and related discussion. We also discuss our identification strategy for two unobserved state variables: addiction and tedium.

5.1. Estimation Strategy and Results

In this research, we estimate the proposed model as a discrete choice model. Specifically, we discretize an online game consumption quantity, decision variable, into ten sections. In this step, we follow the consumption distribution on our dataset. Consequently, we perform the estimation procedure for a ten-choice multinomial model. We also discretize addiction and tedium variables. We discretize addiction into thirty sections and tedium into ten sections. Addiction is required to be further subdivided, according to the forwarding simulation studies. The other state variable, the current level, does not need to be discretized because it has a discretized form from one to eighty. After

[Table 4] Estimation Results

Parameters	Estimates
$\mathrm{I}\{C_{it} = 0\}$ (α_0)	**1.0000** (0.0073)
Consumption (α_1)	**1.0002** (0.0013)
Consumption^2 (α_2)	−**0.0081** (0.0009)
Consumption $*$ Addiction (α_3)	**0.0094** (0.0006)
Consumption $*$ Tedium (α_4)	−**0.0032** (0.0007)
Notes. Standard errors are in parentheses.	

the discretization procedure, we have 24,000 (= 30 × 10 × 80) × 24,000 transition matrices for each decision. We perform the value function iteration to calculate the optimal policy for each parameter set.

Table 4 reports the estimation results of the proposed model by using the maximum likelihood estimation. Directions of all the parameter estimates are as expected. The effect of consumption and the quadratic term of consumption on utility are positive (α_1=1.0002) and negative (α_2=−0.0081), respectively. The interaction effect of consumption and addiction is positive (α_3=0.0094), indicating that the rational addictive behavior does exist in online game consumption. Moreover, the interaction effect of consumption and tedium is negative (α_4=−0.0032), indicating that the negative impact of tedium on utility does exist in online game consumption.

5.2. Identification Strategy

We have two main issues with identification: two unobserved states, addiction and tedium. We argue that addiction can be identified by the relationship between the extent of the increase in consumption and past purchase quantities. Specifically, we can measure the effect of addiction on consumption by the fact that the marginal utility from added consumption of highly addicted users should be larger, and accordingly, the increase in consumption should also be greater. In Section 3-2, we suggest the result of the fixed effects regression utilizing a proxied addiction stock, which provides empirical evidence for our identification strategy.

For the tedium state, we argue that it can be identified by the variation in the data on the cumulative consumption at the same level and decreases in consumption quantity. Cumulative consumption at the same level indicates the same repetitive stimulus for consumers. Therefore, we expect that the negative marginal utility from added consumption of highly tedious consumers should be larger, and accordingly, the decrease in the consumption should also be greater. As with addiction, we suggest the result of the fixed effects regression utilizing a proxied tedium stock in Section 3-2, which provides empirical evidence for our identification strategy.

5.3. Policy Intervention

We perform counterfactual simulation studies using the estimation results of the proposed dynamic structural model. The parameter estimates from the dynamic structural model are policy invariant estimates so that we can use these estimates to quantitatively assess the impact of policy interventions that have never been implemented. In this study, we conduct policy intervention concerning the level-up difficulty that is related to the tedium accumulation process.

We perform forward simulation studies to control the level-up difficulty by changing the value of λ_l, which is the parameter of exponential distribution in the law of motion for level. The simulation results show that the effect of controlling the level-up difficulty is varied by the current level extent. For lower levels, we find that consumption for the higher level-up difficulty (i.e., more complex case) is larger than the actual consumption. It indicates that consumers tend to spend more time playing an online game when they are at the lower levels, given the more complex stimulus. On the contrary, consumption for the higher level-up difficulty is smaller than the actual consumption, for the higher level. It implies that consumers may be struggling to handle the difficulty of a game and, subsequently, negative emotions can arise so that they necessarily reduce their consumption quantities.

The results at lower levels can be explained by prior literature, which focused on the role of complexity. In the context of addiction behavior literature, complexity can be defined as the uncertainty of stimulus. Stimulus with complexity may have more elements, more dissimilarity between components, and lower integration (van Grinsven and Das, 2016). Several studies found that complexity moderates the effects of repeated exposures on preference. That is, consumers' preference for the complex stimulus tended to increase, while preference for the simple stimulus tended to decrease (Berylne, 1970; Saegert and Jellison, 1970; Smith and Dorfman, 1975; Cox and Cox, 1988; Cox and Cox, 2002; van Grinsven and Das, 2016). This can be attributed to complex stimuli having an uncomfortably high level of uncertainty or "arousal potential" for consumers, particularly for early periods. Therefore, repetition of complex stimuli results in a slower learning rate and, subsequently, a slower rate of boredom relative to simpler or familiar stimuli. Then, repeated exposures can reduce excess uncertainty and increase consumers' comfort or preference for stimulus. In the sense that tedium arises when consumers reach certain points of learning, the complex stimulus could postpone tedium effects. Tedium may be accumulated only after a large number of exposures (Galizio and Hendrick, 1972; Cox and Cox, 1988; Janiszewski and Meyvis, 2001; Cox and Cox, 2002; van Grinsven and Das, 2016).

However, this effect could be counteracted if consumers play a game at higher levels, as the simulation results show. When consumers are at higher levels, they could face highly complicated missions which reduce the preference for complexity. This tendency may be further explored by additional research. For example, we can explore various tedious behavior using the model to consider consumer heterogeneity. We can include consumer segments for interaction effects between consumption and tedium in the utility model. Additionally, we can assign a larger or smaller value for a depreciation parameter for tedium as a consumer's tedium sensitivity.

6. Conclusion

We propose a dynamic structural model of rational addiction to explore consumer behavior for online game consumption. Notably, we revise and extend the utility model by introducing a tedium factor to explain consumption reduction and churn patterns that the existing rational addiction model cannot sufficiently explain, and demonstrate that the proposed model can explain online game consumption behavior, analyzing a rich user-level online gaming log data. Moreover, we perform counterfactual simulations related to tedium and level-up difficulties, demonstrating that policies of tedium management can affect consumption decisions and quantities.

Our research contributes to the marketing and economics literature in three ways. First, we propose the extended and revised rational addiction model based on psychology literature on addiction behavior. By including tedium and excluding nuisance parameters that do lack the theoretical background in the existing utility model, we demonstrate that the proposed model can obtain persuasive empirical application results and implications. In addition, we believe that the proposed approach is more appropriate for the original research spirit of Becker and Murphy's (1988) rational addiction framework. Second, the proposed model can provide an empirical framework that can be utilized by the literature following the two-factor addiction model of Berylne (1970), including brand choice models of inertia and variety-seeking behavior and repetitive exposure effects of visual elements such as advertisements and product designs. Particularly, the level is established as a notably influencing factor for the tedium accumulation process, so that related studies can employ and extend their research using this new factor in the literature. Third, we expect that the results of this study provide deeper insights into the literature on online game consumption. The results of our research emphasize the importance of tedium to investigate online game consumption behavior, while most prior studies have focused on motivations for game consumption and addiction (Mehroof and Griffiths, 2010; Kuss and Griffiths, 2011; Xu, Turel, and Yuan, 2012; Beranuy, Carbonell, and Griffiths, 2013). Particularly, our research considers tedium to explain consumption reductions and churn behavior, which can expand the understanding of consumer behavior in the online game industry. Notably, counterfactual simulations show that tedium management by controlling the hurdle of level-up can affect the online game consumption decisions and quantities. We argue that tedium should be included in the model to explore online game consumption behavior. Furthermore, we expect that the results of this study can have social and policy implications, given the severity of youth and young adults' game addiction. Based on our research, we can propose an empirically-founded approach to control youth game consumption effectively. Note that controlling and reducing the consumption of adolescents and young adults do not necessarily result in a negative impact on corporate profits (Nevskaya and Albuquerque, 2019).

We conclude this study with limitations and potential for future research. First, the model in the current study does not consider consumer heterogeneity. In future research, we can perform the model to account for consumer heterogeneity of addiction and tedium. We expect to find notably different consumption patterns between users who are highly addictive or barely addicted or between highly and barely tedious users. Counterfactual simulations including consumer heterogeneity can be performed as well, and more managerial implications can be produced. Second, some of the parameters given in the estimation procedure can be empirically assessed. For example, parameters such as the discount factor of the value function (β), and depreciation parameters in the laws of motion of addiction and tedium, respectively (δ_A, δ_N), could be estimated using a rich nature of user-level usage log data. Finally, the proposed model can be applied to other marketing literature, particularly the literature on the brand choice model, including inertia and variety-seeking behavior and customer relationship management. As mentioned earlier, addiction and tedium have been considered inertia and variety-seeking behavior, respectively, in the brand choice model literature

(Bawa, 1990). Inertia consumer behavior for a specific brand is related to topics in customer relationship management, such as loyalty programs. Most loyalty programs have a grading system for customers, which is similar to the level in the proposed model. We expect this model to be employed in the context of the loyalty programs with customer grades. For example, future research can explore the brand switching behavior of consumers who experience tedium toward the brand, which might be revealed as the drop in customer grades. We can also provide an optimal decision for the number of customer grades to minimize tedium effectively.

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국문초록

본 연구는 온라인 게임 소비 행동을 설명하기 위해 Becker and Murphy (1988)가 제시한 합리적 중독 모형을 토대로 한 구조적 동태 모형을 제시한다. 합리적 중독 모형은 온라인 게임 소비에서 빈번하게 나타나는 과도한 소비, 혹은 중독적인 소비 현상을 설명하기 위하여 제안된 경제학적 모형으로서, “사용에 의한 학습 (learning by doing)”을 근거로 하여 과거 소비 패턴을 통해 중독 수준을 측정, 소비자의 중독적인 소비 행위를 모형화하였다. 그러나 본 연구는 이러한 기존 모형이 중독적인 소비는 설명할 수 있으나, 소비의 감소 또는 이탈 행위를 적절하게 모형화할 수 없다는 사실에 착안하여 기존의 모형을 수정 · 확장하고자 하였다. 구체적으로, Berylne (1970) 등 심리학 문헌에서 중독의 주요 요소로서 제시한 권태(tedium)라는 새로운 요소를 기존 모형에 추가하였다. 소비자가 같은 자극에 일정 수준 이상으로 반복 노출될 경우 중독의 정도를 상쇄하는 요소로서 권태가 발생 · 누적되어, 결과적으로 소비량에도 영향을 미칠 수 있다는 것이다.

본 연구는 시뮬레이션을 통해 본 모형이 온라인 게임 소비 행위의 증감 현상을 제대로 포착할 수 있다는 사실을 확인하고, 상태변수와 가치 함수를 포함한 구조적 동태 모형을 제시하였다. 그리고 온라인 게임의 실제 사용자 레벨 로그 데이터를 이용해 모형을 추정하였다. 그 결과, 소비자의 중독 수준이 현재 소비를 증가시키는 반면, 소비자의 권태 수준은 현재 소비를 감소시키는 경향을 발견하였다. 구조적 동태 모형의 추정 결과를 바탕으로 한 정책 시뮬레이션 결과 또한 제시하였다.

본 연구는 다음과 같은 이론적 · 실무적 시사점을 가진다. 첫째, 기존의 합리적 중독 모형에 권태라는 새로운 요소를 추가한 수정 · 확장 모형을 제안하여 기존의 모형이 설명하기 어려웠던 중독적 소비에서의 감소 또는 이탈 현상을 계량적으로 모형화할 수 있는 접근법을 제시하였다. 둘째, Berylne (1970)의 중독 모형을 계량적으로 분석할 수 있는 틀을 제공함으로써 브랜드 선택 문헌이나 광고 및 제품 디자인의 효과에 대한 문헌 등 해당 모형을 활용해왔던 마케팅 · 경영학 문헌들에 이론적으로 기여할 것으로 기대한다. 셋째, 본 연구의 결과가 온라인 게임 소비 행위에 대한 이해와 통찰을 제공할 것으로 기대한다. 특히, 선행 연구가 게임

소비에 있어 중독 등에 치중하여 진행되어 온 것에 반해, 본 연구는 게임의 중독적 소비에 있어 권태를 주요한 요소로 고려해야 한다는 이론적 근거를 제공한다. 넷째, 본 연구는 청소년 등의 게임 중독이 심각한 사회 문제로 대두되고 있는 상황에서 이를 기업과 정부 입장에서 다양한 정책을 통해 관리할 수 있는 이론적 기반을 제공한다.

주요어: 온라인 게임, 합리적 중독, 권태, 구조적 동태 모형

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