Is Digital Addiction Rational? Investigating Excessive Dependence on Mobile Social Apps

Hyeokoo Eric Kwon
Doctoral Candidate, Korea Advanced Institute of Science and Technology, Business School
85 Hoegi-ro, Dongdaemoon gu, Seoul, Korea, Email: hkkwon7@business.kaist.ac.kr

Hyunji So
Doctoral Candidate, Korea Advanced Institute of Science and Technology, Business School
85 Hoegi-ro, Dongdaemoon gu, Seoul, Korea, Email: namjjong@business.kaist.ac.kr

Sang Pil Han
Assistant Professor of Information Systems, Arizona State University, W.P. Carey School of Business
Tempe, Arizona, Email: sangpil.han@asu.edu

Wonseok Oh
Chair Professor of Information Systems, Korea Advanced Institute of Science and Technology, Business School, 85 Hoegi-ro, Dongdaemoon gu, Seoul, Korea, Email: wonseok.oh@kaist.ac.kr

Is Digital Addiction Rational? Investigating Excessive Dependence on Mobile Social Apps

Abstract

Through the lens of rational addiction theory, this study investigates whether addiction to mobile social apps (e.g., SNS and social games) should be viewed as a rational behavior rather than an uncontrollable, irrational disorder. Understanding digital addiction through the rational choice framework provides important insights into whether addiction-related problems should be addressed through users' self-regulation or government regulation. Most scholarly works on addiction extensively concentrate on physical substances, such as alcohol, cigarettes, or drugs. Our study is unique in its attempt to examine the addictive nature of digital IT artifacts that are non-physical, social, and highly accessible. In contrast to previous works that are based on either self-report surveys or demand estimation at the aggregate level, this study examines addictive behaviors on the basis of consumption quantities. We also explore how addictive these digital goods are relative to physical substances. Furthermore, a nuanced investigation is conducted to determine whether rational addicts consume a substantial amount of addictive substances in pursuit of optimal utility. To empirically validate rational addiction in the context of mobile app consumption, we collect and analyze 13-month, individual-level panel data on the weekly app usage of thousands of smartphone users. The findings suggest that mobile social app users conduct themselves in a forward-looking manner and rationally adjust consumption over time horizons to derive optimal utility. Additionally, both SNS and social game apps more considerably foster dependency than do cocaine and alcohol but are less addictive than caffeine and cigarettes. Compared with light users, heavy users are more predisposed toward rational addiction. Users who are older and more educated and those who are younger and less educated are both less-forward-looking in their consumption of SNS and social games, respectively.

Keywords: rational addiction, digital vulnerability, IT and health impact, mobile apps, econometrics, panel data

1. Introduction

The advent of mobile devices and applications ("apps") as social catalysts may be considered both a blessing and a curse. On the one hand, mobile users are empowered to promote social relationships and assert solidarity with friends through apps such as social games and social network services (SNS), which have become increasingly integrated into their everyday lives. Because of the portability and on-demand accessibility offered by mobile devices, users are perpetually in contact with one another; they can maintain a constant sense of camaraderie and kinship with the people in their social circles. Consequently, the new mobile paradigm has reshaped and, to a certain extent, enriched the social fabric and conventions of society.

On the other hand, the social fever driven by mobile platforms may also be understood as a manifestation of social fear. Notwithstanding the putative benefits of these platforms, sociologists and psychologists are increasingly concerned that the portability, convenience, and ubiquitous connectivity offered by mobile conduits may have adverse ramifications for human behaviors and may reflect underlying feelings of social inadequacy. Heavy or excessive use of social networks and gaming apps on smartphones fosters the formation of habits, that can easily develop into addictive behaviors, similar to the manner by which experimentation transitions to dependence on alcohol, cigarettes, or drugs. According to Flurry, a US-based global market research firm, the average smartphone user spends 2 hours and 38 minutes every day on his or her device to check messages and engage in social network activities, and play games (Khalaf 2013). Even more remarkably, average smartphone users activate their devices more than 80 times a day, which equates to a usage frequency of every 12 minutes (Starr 2014). Two-thirds of UK mobile phone users sleep with their devices by their beds[1]. While eating, attending meetings, crossing the street, or even driving and sleeping, people compulsively check their mobile devices for fear of missing a satisfying "social update." Medical professionals increasingly caution that heavy smartphone dependency can cause severe health crises, including depression, attentional deficits, somatic symptoms, and aggression. As the mobile era

[1] http://www.huffingtonpost.co.uk/paul-twite/the-addiction-that-messes_b_6020450.html

unfolds and approaches its zenith, the apparent addictive preoccupation with and impaired dependency on mobile platforms have become vexing social challenges.

Although research on digital dependency has recently intensified, many questions regarding the issue still remain unanswered. Some of the concerns that have yet to be resolved are how addictive digital goods (e.g., SNS and social games) are relative to physical substances, such as alcohol, cigarettes, or drugs and whether SNS apps (e.g., Facebook) more considerably foster compulsive reliance than do social game apps. In addition, our understanding is limited as to what factors cause digital addiction and how such problems can be prevented or, at least, mitigated. Should the government intervene and enforce laws to mitigate the public health risks arising from digital addiction? Alternatively, should we allow users to self-regulate their consumption of highly addictive digital goods? Anecdotal evidence suggests that legal sanctions are ineffective measures for ending digital dependency. The extant literature has provided no conclusive recommendations on specific solutions to digital addiction.

In academic circles, the "nature versus nurture" controversy that surrounds addictive behaviors continues to intrigue scholars and medical professionals. Researchers who support the "nature" perspective have long espoused an exclusive definition of addiction as an acute type of irrational behavior and as a chronic disease that requires psychological and medical treatment. This perspective was expanded by Nobel Laureate economist Gary Becker and his colleague in their seminal article, "Theory of Rational Addiction." Defying conventional knowledge, the authors argue that addiction to substances (e.g., cigarettes and alcohol) can also be explained by utility-maximizing rational human behavior that can be "nurtured" (i.e., controlled) by exogenous factors (e.g., prices). This reasoning is the essence of rational addiction theory (Becker and Murphy 1988), which holds that addicts are rational in that they anticipate the future consequences of their current consumption and act wisely to arrive at a choice with maximum utility. For example, when addicts expect the future prices of addictive goods to rise, they reduce their current consumption of these goods, because the higher price will diminish the marginal utility of current and future consumption. This frame of reference starkly contrasts with the "myopic" theory of habit formation in which one's current assessment of utility depends solely on the past and current consumption of addictive goods (Pollak 1970, 1976).

In this study, we explore the mobile “app-diction” phenomenon (defined as the excessive dependence on mobile social apps) through the lens of rational addiction theory. Building on the theoretical insights offered by Becker and Murphy (1988), this study derives an analytical framework that enriches our understanding of rational addiction to mobile social apps. We draw on this rational choice framework to offer a holistic view on individuals’ addictive behaviors across various time horizons (i.e., past, present, and future) over which they attempt to maximize utility from their intertemporal consumption choices. In investigating “self-interested” behaviors wherein individuals endeavor to seek pleasure and avoid discomfort, we adopt this utilitarian approach in the hope of providing genuine insights into the etiology of digital dependency and vulnerability. This economic perspective may also provide nuanced knowledge about the fundamental mechanisms and underlying dynamics that contribute to the digital addiction that is beginning to affect public health today.

To validate empirically whether users of social apps exhibit rational addictive behaviors, we gathered and analyzed 13-month, individual-level panel data on weekly usage of mobile social apps by thousands of smartphone users. To date, most scholarly works on addiction are based on either self-report surveys or demand estimation at the aggregate level. Although valid and useful, these approaches may be susceptible to structural biases and inaccuracies. The survey-based approach merely reflects users’ perceptions and not actual behaviors, whereas aggregate demand estimation shows quantities purchased and not the actual consumption of purchased goods. Quantifying precisely how much individuals smoke and drink alcohol would be extremely difficult, if not impossible. We significantly improve the quality of consumption measurement by tracing individuals’ real app consumption, which is determined in seconds over a 13-month period. To the best of our knowledge, this study is among the first to examine addictive behaviors on the basis of actual consumption quantities. Specific research questions in the current work are as follows:

- Do users exhibit rational addictive behaviors when consuming mobile social apps?
- Are digital goods more addictive than traditional physical substances (e.g., alcohol, cigarettes, caffeine, or drugs)? Do social games more significantly induce susceptibility to addiction than SNS?

- Which demographic groups (e.g., by age, gender, and income) are more vulnerable to rational addiction to mobile social apps? Are heavy users more vulnerable to rational addiction than are light users?
- Should digital addiction and vulnerability be self-regulated or government-regulated?

The empirical regularities that we observe in the data analysis suggest that users exhibit strong rational addictive behaviors when using mobile social apps. We also find that addiction vulnerability is strongly associated with the extent of consumption inertia manifested through reinforcement effects, the sensitivity to social liquidity (i.e., network effects), and the degree of propensity for adopting a forward-looking mindset. However, rational addictive behaviors are more pronounced in heavy users than in light users, suggesting that in certain situations, rational addicts are exposed to great risk because they are easily encouraged to heavily consume digital substances up-front in pursuit of optimal utility. Furthermore, digital substances are as addictive as notoriously habit-forming physical substances. The extent of rational addiction is more pronounced in users of social networking apps than in users of social game apps. In addition, addictive behaviors towards SNS are more rational in nature for the younger, high-income groups because the temporality that underlies their consumption is more strongly oriented towards the future. Our findings collectively suggest that concern over addiction to mobile social apps is driven by many factors, but we also derive evidence that effectively addressing these digital addiction issues is feasible through the use of basic economic principles.

2. Theoretical Background

Addiction has long been understood as pertaining to uncontrollable and irrational behaviors motivated by the desire to experience pleasurable and euphoric effects despite their potentially harmful consequences (Pollak 1970, Yaari 1977). Medical scientists have treated addiction as a chronic disorder caused by a biological or neurological predisposition, whereas socio-psychologists have evaluated it as an irrepressible response that is engendered by the interplay between heredity and social environment (Peele 1985). Academic communities have actively showcased addiction issues and their negative effects on humanity.

A deficiency worth looking into, nonetheless, is that most scholarly works on addiction are extensively concentrated on physical substances [e.g., drugs (Everitt and Robins 2005), cigarettes (Naqvi et al., 2007), alcohol (Herz 1997), and gambling (Blaszczynski and Nower 2002)], whereas minimal attention is paid to "digital addiction," wherein users are "caught in the Net" and unable to curb the compulsive use of digital devices (Young 1998).

2.1. IT and Mobile Addiction

The extant literature on IT-triggered addiction focuses primarily on the antecedents and consequences of digital addiction. Young (1998) finds that Internet addiction can be as detrimental as substance addiction because it can throw one's life out of balance and cause physical damage. This survey-driven study reveals that Internet addicts suffer from severe social, professional, and affective impairment and disruption. Drawing from the uses and gratifications and the play theories of mass communication, Morris and Ogan (1996) establish a theoretical foundation for Internet addiction, with special attention paid to the social and psychological origins of human needs. Griffiths (2000) theorizes on Internet addiction in terms of core elements (i.e., salience, mood modification, tolerance, withdrawal, conflict, and relapse) that form behavioral addiction. Kim et al. (2008) suggest that self-control is negatively related to online game addiction, whereas aggression and narcissistic identity are positively associated.

An emerging body of work has recently called for a new understanding of mechanisms and an innovative treatment of mobile addiction. Problematic behaviors associated with the excessive use of mobile phones include the "nomophobia" disorder (short for no-mobile-phone phobia) (King et al., 2010), text message overreliance (Igarashi et al. 2008), and phantom vibration syndrome (Rothberg et al. 2010). Bianchi and Phillips (2005) reveal that extraversion and low self-esteem are significant psychological predictors of heavy mobile phone use. Using diagnostic tools, Choliz (2010) identifies the main causes and consequences of mobile phone dependence and presents detailed health implications related to technological addiction. On the basis of psychiatric perspectives, Stone (2014) avers that attachment to smartphones is similar to other forms of addictive behavior because it involves a dysregulation of dopamine - a neurotransmitter that helps control the brain's reward and pleasure centers. Some mild remedies for smartphone addiction include "resetting your brain", which involves taking nature walks, watching clouds, or exercising for a few minutes (Thibodeau 2012). Some extreme measures are "digital detox programs," wherein participants engage in activities such as archery, sing-a-longs, and meditative breath workshops, all without the use of a smartphone or other mobile devices (Stone 2014).

Although varied in scope and contexts, most addiction studies, including all the works noted earlier, seem "addicted" to the use of survey-based approaches that must depend heavily on subjective, perceptual, and often inaccurate human cognition (Fowler 1992). Furthermore, medical and psychological studies on addiction are all grounded in a type of "disease model," in which compulsive and irrational behaviors originate from neurological, genetic, and biological causes that can be cured only by lifelong abstinence. This nature oriented standpoint of addiction, however, has been challenged by Becker and Murphy (1988) who broke new ground in the study of human behavior.

2.2. A Rational Choice View of Addiction

The defining features of addictive behaviors, such as irrationality, compulsion, overindulgence, and loss of control, have been questioned by Becker and Murphy (1988). Using the seminal findings of Stigler and Becker (1977) and Iannaccone (1984) as a prelude to their elegant analytics, Becker and Murphy (1988) proposed the rational addiction model in which addicts are not "myopic" but rational. Rational, farsighted addicts anticipate the future consequences of their current behaviors and act prudently in their own best interests (i.e., by formulating optimal consumption plans) to maximize discounted utility. The most essential aspect of the theory is that, by weighing the effects of their actions on the future, addicts, who have full knowledge of the consequences of their addiction, strategically calculate the expected benefits (e.g., utility gains from taking drugs) against costs (e.g., negative impacts on health). They arrive at a rational choice that maximizes utility based on their stable preferences. For example, drug addicts may be cognizant that their current drug use will stimulate greater future drug consumption and that continued drug use will result in negative consequences (e.g., adverse health). Nevertheless, they may appraise the utility gained from taking drugs as outweighing the discounted reduction in utility arising from negative consequences. Using this example and many others, Becker and Murphy (1988) construe addiction as rational, utility-maximizing behavior, just like any other actions based on economic considerations.

To illustrate further, in previous myopic models of addictive behaviors, addicts neither consider the future consequences of their current consumption nor factor future prices of addictive goods into their current consumption decision-making (Becker and Murphy, 1988). Instead, they choose current consumption based primarily on past consumption. This myopic perspective regards addiction as merely the positive interaction and complementarity between past and current consumption of addictive goods, without reference to future consumption or prices.

As opposed to this backward-looking, myopic model, the rational addiction framework maintains that addicts decide on current consumption with future consumption and future utility in mind in order to maximize discounted utility. This forward-looking paradigm, which falls under the umbrella of the rational choice model (Calvert 1985), centers on the dynamics of current consumption in response to anticipated future prices of addictive goods. For example, rational addicts may proactively reduce their current consumption of tobacco when they anticipate the prices to rise in future. They recognize that the anticipated price increase will lower the marginal utility of their current and future consumption. In contrast, myopic addicts do not cut their current consumption in response to expected increases in future prices.

In constructing the rational addiction model, Becker and Murphy (1988) assume that an individual's utility at time t depends on three elements: consumption of addictive goods C_t, addictive stock A_t, and consumption of other goods Y_t. In addition, these authors explicate three distinctive aspects of addiction: withdrawal, reinforcement, and tolerance. Withdrawal corresponds to a decline in current utility due to reduced current consumption. Reinforcement is evident when high levels of past consumption prompt the desire for current consumption and increase the marginal utility of current consumption. Finally, increased tolerance shows that the greater the addictive stock (i.e. cumulative past consumption of the addictive substance), the lower the current utility (Becker and Murphy1988). The idiosyncrasies of addiction give rise to a behavioral pattern in which past consumption of addictive goods induces current consumption by influencing the marginal utility of both current and future consumption (Becker and Murphy 1988). This inter-temporal, dependent demand structure, often called "adjacent complementarity" (Ryder and Heal 1973), epitomizes the key conceptual building-blocks that underlie the rational addiction model. Consumers become addicted if their past consumption positively affects their current consumption. An addictive behavior is thought to be rational when current consumption is positively dependent on future utility and consumption.

In a subsequent study, Becker et al. (1994) thoroughly scrutinize the model of rational addiction by conducting an empirical investigation of the effect of higher future cigarette prices on current consumption of cigarettes. In their empirical framework, they assumed that addicts make rational decisions about their consumption of both non-addictive and addictive goods within their lifetime budget. The model assumes a quadratic utility function in $C_t, A_t,$ and Y_t to elicit the demand function (see Becker et al. (1994, p.398) for derivations). Finally, they identify the resulting demand structure of addictive goods, C_t, which denotes current consumption as a function of both past and future consumption, and the current price of the addictive goods, P_t:

$$C_t = \theta_0 + \theta_1 C_{t-1} + \theta_2 C_{t+1} + \theta_3 P_t \tag{1}$$

where $\theta_1 = -u_{CA}/\{u_{cc} + u_{AA}/(1+r)\}$, $\theta_2 = \theta_1/(1+r)$, $\theta_3 = r/\{u_{cc} + u_{AA}/(1+r)\}$ and r is an interest rate.

Various scholars have since leveraged the empirical formality specified in Equation 1, testing the theory of rational addiction by estimating the following model parameters: $\theta_1$and θ_2. The positive effect of past consumption on current consumption (θ_1) signifies addiction, and the addictive behavior is considered rational when the effect of future consumption on current consumption (θ_2) exhibits the same direction as θ_1. Most empirical studies find significant and positive values for θ_1 and θ_2 in diverse habit-forming contexts, including consumption of cigarettes (Becker et al. 1994), alcohol (Baltagi and Griffin 2002), cocaine (Grossman and Chaloupka 1998), opium (Liu et al. 1999), caffeine (Olekalns and Bardsley 1996), and gambling (Mobilia 1993).

3. Rational Addiction to Mobile Social Apps

This study extends the model of rational addiction (Becker and Murphy 1988) to investigate whether addiction to social apps (e.g., SNS and social games) follows the patterns of utility-maximizing, rational behaviors. Addiction to social apps can be viewed as one form of technological addiction (Turel et al. 2011). We refine the analytical and empirical components of the frameworks architected by Becker and Murphy (1988) and Becker et al. (1994) in the context of mobile social apps, which are non-physical and monetary-free commodities. We test the models on panel data gathered weekly, examining app consumption behaviors at the individual user level. This approach is in contrast to those of previous studies in which aggregate-level and yearly or quarterly data were used.

3.1. Social Exchanges as Economic Actions

Social exchange theory (Homans 1958), which originates from the scientific traditions of neoclassical economics paradigms, offers a conceptual foundation for comprehending social relationships through economic principles. This canonical theory maintains that social behaviors can be construed as the upshot of negotiated exchange processes, in which rational actors navigating in social situations select behaviors that maximize their own self-interests. If the reward or utility derived from social interaction outweighs the punishment or cost, they cultivate the ensuing relationship. Under excessively high cost, however, they suspend interpersonal associations. Regarded as an economic metaphor for social relationships, social exchange theory is underpinned by several key premises. First, individuals engaging in social relationships can rationally and successfully gauge the costs and benefits of social exchanges. Second, individuals involved in exchange processes rationally seek to maximize payoffs or rewards to satisfy their basic social needs. Finally, exchange processes and outcomes alter power and privilege structures in social groups because of the competitive nature of social systems.

In our model, the act of consuming social apps (e.g., exchanging messages through SNS or playing social games) is viewed as an enacted exchange process, in which app users endeavor to maximize payoffs by enhancing their social presence and privileges within the time frame in which interaction takes place. Users of social apps are forward-looking and rational in that they anticipate the future consequences of their current app consumption. Their social exchange relationships are determined by strategic reward-cost calculations. Consistent with the notion of adjacent complementarity, the current consumption of social apps increases the marginal utility of future consumption; as a result, users increase their current app consumption when they expect social liquidity[2] to rise in the future. Users consuming social apps are therefore typified with a pervasive drive to form and maintain stable social bonds and attachments, which are reinforced through the use of social apps.

3.2. Social Liquidity and Exchange Dynamics

In Becker and Murphy's (1988) model, the price of addictive substances regulates addicts' inter-temporal consumption preferences. That is, the anticipated future prices of addictive commodities influence current consumption because they affect future stocks and consumption patterns. As indicated in the model, governments, for example, can "effortlessly" motivate smokers to lessen their current cigarette consumption by pre-announcing a cigarette tax increase. In this scenario, increased future prices negatively affect current consumption because future consumption and utility may decrease. Becker et al. (1994) find that a 10% increase in cigarette prices can reduce current consumption by as much as 7.5% in the long run. Moreover, a 10% price increase in one period reduces consumption in the previous period by 0.6% and in the subsequent period by 1.5%. These correlation patterns demonstrate the inter-temporal associations in cigarette demand that result from rational addictive behaviors.

For addicts to mobile social apps, no direct payment is necessary to consume the apps once they have been downloaded and installed onto mobile devices. In fact, mobile apps can be distinguished from physical

[2] Details on social liquidity are presented in the next section.

addictive goods (e.g., cigarettes and alcohol) in several ways. Most mobile apps are available free of charge, but most physical addictive goods are not. In addition, while negative health-related consequences from excessive doses of physical addictive substances can be immediately recognized, physical damage caused by heavy consumption of mobile apps may be relatively difficult to notice in the short term. Moreover, mobile apps can be downloaded and consumed by anyone, anywhere, whereas physical addictive goods, like cigarettes, can be purchased and consumed only by adult consumers in specific areas. Finally, interaction and reciprocity stimulate the consumption of social mobile apps, such as SNS and social games, but such social intercourse, although relevant, is less important in the consumption of physical addictive products. These inherent characteristics unique to mobile apps lure consumers even more than do physical substances; users can therefore become even more easily addicted to the free, digital social mobile apps.

Just as price affects the consumption of physical commodities, social liquidity (i.e., the ease with which one can establish interpersonal relationships) determines how much users consume the social commodities (e.g., social apps). In financial markets, market liquidity, defined as how easily an asset can be traded and converted to cash with minimal impact on price, often has a significant effect on traders' willingness to engage in trading activities. If all else is equal, the greater the liquidity within a market, the larger the benefits investors can gain. The size of the market (e.g., the number of active traders) often serves as a key catalyst that galvanizes the degree of market liquidity (Pagano 1989). Furthermore, because of the network externality effect, the principle of "liquidity attracts liquidity" is often demonstrated in the financial market (Roll et al. 2009). In this respect, utility from consuming social apps for users is contingent on the amount of social liquidity they perceive to be available. This is similar to the notion of network effects (Katz and Shapiro 1985) in which a user's utility derived from consuming a particular social app escalates exponentially as the number of other people using it increases. Recently, several studies focusing on online-based social networks (e.g., Susarla et al. 2012, Zeng and Wei 2013) have demonstrated the important role such positive consumption externalities play in disseminating user-generated content across social network platforms (e.g., YouTube and Flickr). Consequently, rational, forward-looking app users form expectations about changes in social liquidity in future periods and establish optimal consumption plans that maximize their utility in the present.

Following Freud's (1930) lead in his research on social dynamics, theorists regard the need to belong and social attachment as intrinsic human motivators (Baumeister and Leary 1995). In certain respects, social platforms (e.g., Facebook) can be viewed as social markets where individuals seek social attachments by "trading" (i.e., making or breaking) interpersonal relationships. Relationships may be newly formed, strengthened, and often ended on Facebook and in social games. In essence, several features unique to these platforms, such as Facebook Likes and In-App Currency/Credit Exchanges, are designed to increase social liquidity. These artifacts constantly foster and lubricate social exchanges through shared emotions, thoughts, and gossip. Users consume social apps to form or maintain lasting, positive, and affectively pleasant relationships with other people within or across their usual social boundaries. Furthermore, they often endeavor to enhance their social presence and authority by receiving recognition and soliciting caring comments from others. The more users involved and the greater the social liquidity within a platform, the greater the utility derived from the exchanges. As a consequence, social liquidity (i.e., the number of users available with whom social relationships can be cultivated) strongly influences how actively individuals engage in online social activities (Fang et al. 2013). Social liquidity also affects their ability to utilize their time resources efficiently for the purpose of forming and maintaining interpersonal relationships. Therefore, rational app addicts will anticipatorily increase their current consumption of social apps when they expect future social liquidity to increase. They appraise the utility gained from consuming social apps as outweighing the discounted reduction in utility arising from the negative consequences of doing so (e.g., escapism, procrastination, preoccupation, poor time-management).

3.3. An Analytical Model

Based on the discussion above, we posit that an individual's utility depends on the factors specified in Equation 2.

$$U_{i,t} = u[C_{i,t}, Y_{i,t}, A_{i,t}, L_t], \tag{2}$$

where $C_{i,t}$ is the amount of social app consumption of individual *i* at time *t*. In our context, no direct monetary cost is associated with consuming mobile social apps, but a user incurs an opportunity cost, i.e., the value of what other activities the user could have done during that time. $Y_{i,t}$ refers to the time spent on these outside options of *i* at time *t*. $A_{i,t}$ indicates the amount of addictive stock of *i* at time *t*. Finally, L_t reflects the degree of social liquidity at time *t*. Further, we assume that the utility function is concave with negative second derivatives, and that consumption of addictive goods does not affect the marginal utility of outsides goods consumption.

$$U_{CC} < 0, U_{AA} < 0, U_{YY} < 0, U_{CY} = 0, U_{AY} = 0 \tag{3}$$

As pointed out earlier, there are three characteristics of addictive consumptions—withdrawal, tolerance, and reinforcement— that are represented in mathematical forms below.

$$U_C > 0, U_A < 0, U_{CA} > 0 \tag{4}$$

In addition, we assume that social liquidity L_t positively affects the marginal utility of app consumption, and that addictive stock does not affect the marginal effect of social liquidity on utility.

$$U_{LC} > 0, U_{LA} = 0 \tag{5}$$

W in Equation 6 represents the total amount of time (i.e., 24 hours per day) allowed to each individual on any given day, denoting a time budget constraint. This constraint is similar to the budget constraint in the Becker-Murphy model.

$$C_{i,t} + Y_{i,t} = W \tag{6}$$

where *W* is the length of time period *t*. Because of the time budget constraint, the utility function can be restated as shown in Equation 7.

$$U_{i,t} = u[C_{i,t}, A_{i,t}, L_t] \tag{7}$$

In Equation 8, each individual app user chooses $C_{i,t}$ to maximize the sum of lifetime utility discounted at the rate *r* subject to the time budget constraint in Equation 6.

$$\max_{C} \sum_{t=1}^{\infty} (1+r)^{-t} u[C_{i,t}, A_{i,t}, L_t] \tag{8}$$

where r is an interest rate. Consistent with the rational addiction model, addictive stock is assumed to be equal to the consumption of previous periods (Equation 9). In addition, a quadratic utility function in $C_{i,t}, A_{i,t},$ and L_t is employed to derive the empirical demand function (Equation 10).

$$A_{i,t} = C_{i,t-1} \tag{9}$$

$$U_{i,t} = a_1 C_{i,t} + a_2 A_{i,t} + a_3 L_t + u_{cc} C_{i,t}^2/2 + u_{AA} A_{i,t}^2/2 + u_{LL} L_t^2/2 \tag{10}$$
$$+ u_{CA} C_{i,t} A_{i,t} + u_{CL} C_{i,t} L_t + u_{LA} L_t A_{i,t}$$

By substituting Equations 9 and 10 into Equation 8, a utility-maximizing demand function subject to the time constraint can be derived. Equation 11 represents the associated first-order condition.

$$\partial u[C_{i,t}, A_{i,t}, L_t]/\partial C_{i,t} + \partial u[C_{i,t+1}, A_{i,t+1}, L_{t+1}]/((1+r)\partial C_{i,t}) = 0 \tag{11}$$

The resulting demand function of social apps represents current consumption, $C_{i,t}$, as a function of past ($C_{i,t-1}$) and future consumptions ($C_{i,t+1}$), as well as the current degree of social liquidity, L_t

$$C_{i,t} = \delta_0 + \delta_1 C_{i,t-1} + \delta_2 C_{i,t+1} + \delta_3 L_t \tag{12}$$

where $\delta_1 = -u_{CA}/\{u_{cc} + u_{AA}/(1+r)\}$, $\delta_2 = \delta_1/(1+r)$, $\delta_3 = -u_{LC}/\{u_{cc} + u_{AA}/(1+r)\}$, and r is an interest rate.

Based on Equations 3 and 4, a positive value of δ_1 indicates that a good is addictive. Because δ_2 of Equation 12 is derived from the second term of the first-order condition (Equation 11), a positive value of

δ_2 indicates that an addiction is the result of rational forward-looking behavior. According to Becker and Murphy (1988, p.682), individuals with a greater preference for the present are more subject to becoming addicted and behaving myopically than those with a greater preference for the future. Thus, the ratio of the estimated coefficients on past consumption to those on future consumption, δ_1/δ_2, implies the rate of time preference. As $r = (\delta_1/\ \delta_2) - 1$, the estimated interest rate captures the rate of time preference. A high (low) rate of *r* implies myopic (less myopic or more rational) behavior.

4. Empirical Validation

We provide a brief overview of the empirical background and variables derived from the data and illustrate our econometric specification models. In addition, we discuss how we identified the estimates of the parameters, after which we present our findings.

4.1. Empirical Context and Data Description

We constructed a panel dataset consisting of information on app time use for two mobile social apps—a widely used social networking app (Facebook) and a popular social gaming app (Anipang). Facebook is a social networking service (SNS), important functions of which are to build and maintain relationships. For example, users may become Facebook friends, sharing their thoughts, opinions, photos, videos, and links to other sites they find interesting. Anipang is a mobile messaging, platform-based, social puzzle game. The mobile messaging platform allows users to find friends who are also playing the puzzle game. The basic structure of Anipang is similar to another popular social puzzle game—Candy Crush. After completing a round, players can check their ranking compared to those of their friends in a social messaging app with a leader board for those who play the game. Each game only lasts for one minute. To continue the game, players must acquire in-app currency in the form of "hearts." Players may choose to wait several minutes to get more hearts. Alternatively, players give each other hearts as gifts or get more hearts by inviting friends on the social messaging app list to join the game. These mechanisms encourage users to communicate continuously with other users.

The data used in this study was provided by Nielsen KoreanClick, a Korean market research company specializing in online and mobile internet audience measurement. Audience measurement measures how many people are in an audience and how long they remain, usually in relation to television viewership (e.g., Nielsen ratings), but also in relation to increasingly, traffic on websites and mobile apps. Nielsen KoreanClick maintains a panel of mobile app users, ranging in age from 10 to 70 years old, who are selected by stratified sampling. After individuals agree to be panel members, they download and install a Nielsen Mobile App on their mobile devices. This app runs in the background and collects data on panel members' use of mobile apps and the mobile web even while disconnected. The meter app regularly transmits encrypted log files to a server via a secure cellular connection or Wi-Fi. We used data collected between October 1, 2012 and October 27, 2013 (56 weeks). The data for 3,616 panel members included individual-level, weekly information on these users' activities on the aforementioned mobile social apps throughout the sampling period. In addition, we acquired individual-level information on user demographics such as age, income, and education.

4.2. Model Estimation and Identification

To identify the impact that past and future consumption of a particular mobile social app has on the current consumption at the individual user level, we consider the following econometric model:

$$C_{i,t} = \delta_0 + \delta_1 C_{i,t-1} + \delta_2 C_{i,t+1} + \delta_3 L_t + \mu_i + \lambda_t + u_{it} \tag{13}$$

where the subscript i denotes the i-th user and the subscript t denotes the t-th week. $C_{i,t}$ is the consumption of a mobile social app (measured in seconds) by user i at time t. L_t is the number of active users in the platform during time t. Finally, μ_i is a user-specific effect, λ_t is a week-specific effect, and u_{it} is a remainder disturbance.

Use of the rational addiction model in the context of mobile social apps poses several endogeneity problems due to the presence of lead and lag with respect to the dependent variable, the potential simultaneity between the number of active users and the dependent variable, and a potential serial correlation among the disturbances. In many models using dynamic panel data (e.g., Arellano and Bond 1991), only $C_{i,t-1}$ appears and not $C_{i,t+1}$. Hence, we cannot use the usual prescribed instruments, as the result would be two period lagged variables—$C_{i,t-2}$. If the $u_{i,t}$s are serially correlated, even higher lagged $C_{i,t}$'s —($C_{i,t-3}$, $C_{i,t-4}$, and so forth)—are not valid instruments for our model. However, we found that no serial correlation of $u_{i,t}$s is evident in our empirical context; thus, we use $C_{i,t-3}, \ldots, C_{i,t-k}$ as instruments in this study. In addition, the Becker and Murphy model suggests that we use both a lagged and a future number of active users—(L_{t-1}, and L_{t+1})—as measurement instruments. However, these instruments are invalid in our empirical context because the number of active users can be correlated with a disturbance, thus introducing another source of endogeneity. Instead, we use a second lagged variable—L_{t-2}—as an instrument to represent the current number of active users. Finally, we add a lagged variable representing consumption of active users for a different mobile social app $C'_{i,t-1}$ to the set of instruments in the Becker and Murphy model. The rationale for using these instruments is that the lagged consumption of active users $C'_{i,t-1}$ for another app is likely to be correlated with the lagged consumption $C_{i,t-1}$ for the focal app (i.e., joint app time use decisions across multiple apps during the same time period) but less likely to be correlated with current consumption $C_{i,t}$.

To ensure that this set of instruments was valid for use with our data and met the requirements necessary for analyzing panel data, we performed the Hansen test for over-identification and the difference-in-Hansen test of exogeneity on subsets of instruments and found that our instruments were valid at the 10% significance level. In addition, we conducted AR tests for autocorrelation of the residuals to ensure the appropriateness of our lagged endogenous variables. By construction, the residuals of the differenced Equation 13 should possess serial correlation due to lead and lag of the dependent variable. That is, we should reject Arellano-Bond tests for AR(1) and AR(2). However, if the assumption of serial independence in the original errors is warranted, the differenced residuals should not exhibit significant AR(3) behavior. Our results were consistent with our expectations in that we rejected the Arellano-Bond test for AR(1) and AR(2), but could not reject it for AR(3) at the 5% significance level. Hence, this set of instruments was deemed appropriate for use with the panel data.

4.3. Main Results

Table 1 shows the main results of the model obtained using the difference generalized method of moments (GMM) estimation. We find that $\hat{\delta}_1$ and $\hat{\delta}_2$ are positive and statistically significant for both social apps, which indicates that users exhibit rational addictive behaviors when utilizing mobile social apps. Interest rates are also positive and statistically significant for both social apps, demonstrating that, in our context, the reinforcement effect from past consumption is larger than the forward-looking rationality of future consumption. For example, Column 1 shows that the interest rate is positive (0.0823) due to the larger coefficient of past consumption (0.434) than the coefficient of future consumption (0.401). Similarly, in Column 2, the coefficient of past consumption (0.469) is larger in magnitude than the coefficient of future consumption (0.463); thus, the interest rate is positive (0.0130). For both social apps, exogenous factors that promoted past consumption by 10 percent would increase current consumption by between 4 and 5 percent. Similarly, a shock that would increase consumption by 10 percent in the future would lead to a rise of between 4 and 5 percent in current consumption.

We find that $\hat{\delta}_3$ is positive and statistically significant for both social apps (1.373 and 0.470 for SNS and social games, respectively), which suggests that as social liquidity grows, rational app addicts increase their consumption of social apps. For example, SNS apps allow people to communicate with each other socially. They can exchange messages and receive automatic notification when their friends update their profiles. They can also regulate their app consumption according to the number of active users on the platform. In the context of social game apps, leader scoreboards help users learn about and predict the usage patterns of their friends more accurately and manage their inter-temporal consumption wisely. Furthermore, players often invite their friends in order to be able to play more. Such incentives built into social games can also make players regulate their consumption rationally.

Table 1 GMM Estimates of Rational Addiction Model

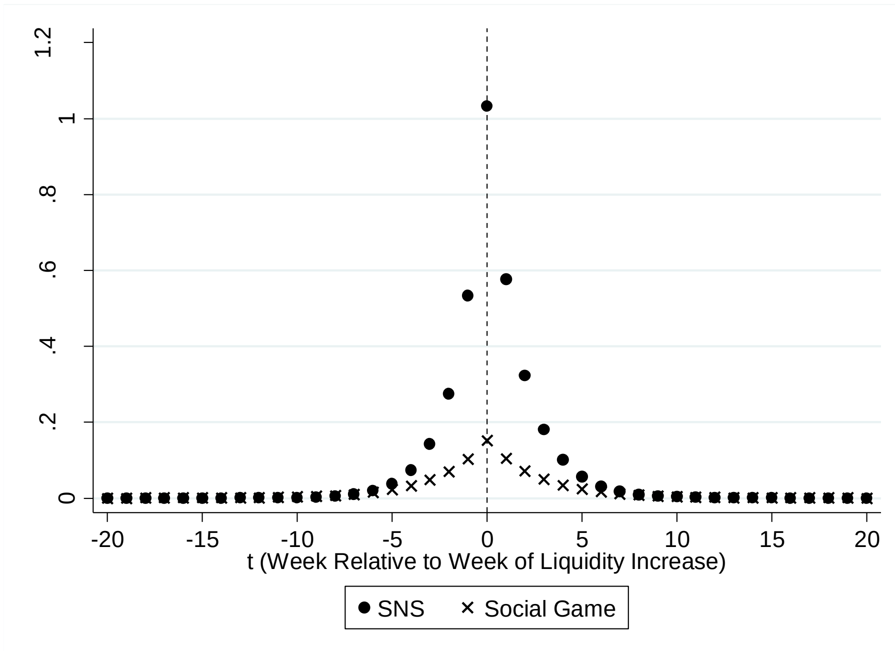
	$C_{i,t}$	
Variables	Social Networking Service Facebook	Social Game Anipang
$C_{i,t-1}$, $\hat{\delta}_1$	0.434***	0.469***
	(0.0267)	(0.00869)
$C_{i,t+1}$, $\hat{\delta}_2$	0.401***	0.463***
	(0.0122)	(0.0198)
L_t, $\hat{\delta}_3$	1.373***	0.470***
	(0.175)	(0.169)
Interest rate, r	0.0823	0.0130
Observations	104,975	50,247
Number of users	2,710	1,824

*Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in parentheses. For SNS, we use [Ci,t-4,…, Ci,t-41] and [Lt-3,…, Lt-40] and social game app C′i,t-1 as instruments. For social game, we use [Ci,t-4,…, Ci,t-16] and [Lt-3,…, Lt-15] and SNS app C′i,t-1 as instruments.*

Drawing on the insights provided by Becker et al. (1994), we identify three types of elasticity related to inter-temporal liquidity to quantify how changes in past, current, and future social liquidity may affect the volume of current consumption. Figure 1 presents a schematic representation that visualizes the effects of changes in liquidity in period $\tau\ (= 20)$ on app consumption in period $\tau \pm t\ (t \geq 0)$ with respect to the two types of social apps. Specifically, Figure 1 displays percentage increases in app consumption in period t in response to a 1 percent increase in liquidity in period $t = 0$. To illustrate further, $t = 0$ denotes the effects of changes in current liquidity on current consumption. While $t = -5$ denotes the extent to which changes in future liquidity five weeks after the current period $(t = 0)$ affect current consumption $(t = -5)$, $t = 5$ indicates how variations in past liquidity five weeks prior to the current period $(t = 0)$ influenced the volume of current consumption $(t = 5)$.

Figure 1 portrays several noteworthy empirical regularities surrounding the differential effects of social liquidity on usage of the two types of social apps. Contrary to common belief, users of SNS are more sensitive to changes in social liquidity than users of social games. In addition, users of both apps become most responsive to the current liquidity change. Furthermore, as opposed to social game users who react similarly to the same level of liquidity increases in both future and past periods, users of SNS appear to be more sensitive to such increases in past periods than those in the future. This is because estimated coefficients on past consumption is greater than those on future consumption in the SNS context $(\delta_1 > \delta_2)$, i.e., users of SNS have a greater time preference for the present than for the future.

Figure 1 Social Liquidity Elasticity



4.4. Physical Addiction vs. Digital Addiction

Although an individual can discern the addictive nature of mobile apps, he or she may not be cognizant of how addictive these digital goods are relative to physical substances, such as cigarettes and alcohol. Similarly, little is known about individuals' forward-looking behaviors with respect to the consumption of mobile apps versus the consumption of physical addictive goods. Figure 2 schematically represents the extent of addictiveness and rationality across a variety of addictive goods, including social games and SNS. This direct comparison based on the magnitude of coefficients should be interpreted with caution because we use individual-level, consumption data rather than aggregate-level sales data. We also leverage social liquidity, rather than price, as a modulator that regulates inter-temporal consumption choices. Nevertheless, given that our estimation approaches are more conservative than those employed in other studies, the comparison scheme remains valid and provides a useful index for understanding the extent of addictiveness across diverse substance categories.

The schematic representation exhaustively illustrates the revealing differences between social apps and physical addictive substances. In terms of addictiveness, both SNS and social game apps more considerably foster dependency than do cocaine and alcohol, but are less addictive than caffeine and cigarettes. When rationality is used as a criterion, SNS appears to more strongly induce susceptibility to rational addiction than do caffeine and cigarettes; however, SNS occasions vulnerability less intensively than do cocaine and alcohol. Social game apps more substantially give rise to rational addiction than do caffeine, cigarettes, and cocaine but strongly stimulate such dependence than does alcohol. These results collectively suggest that digital substances (e.g., SNS and social games) are as addictive as notoriously habit-forming physical substances (e.g., alcohol, caffeine, and cigarettes) (see Table 2 for detailed statistical comparisons).

Figure 2 **Degree of Reinforcement (δ_1) and Forward-Looking Behavior (r) Across Different Goods**

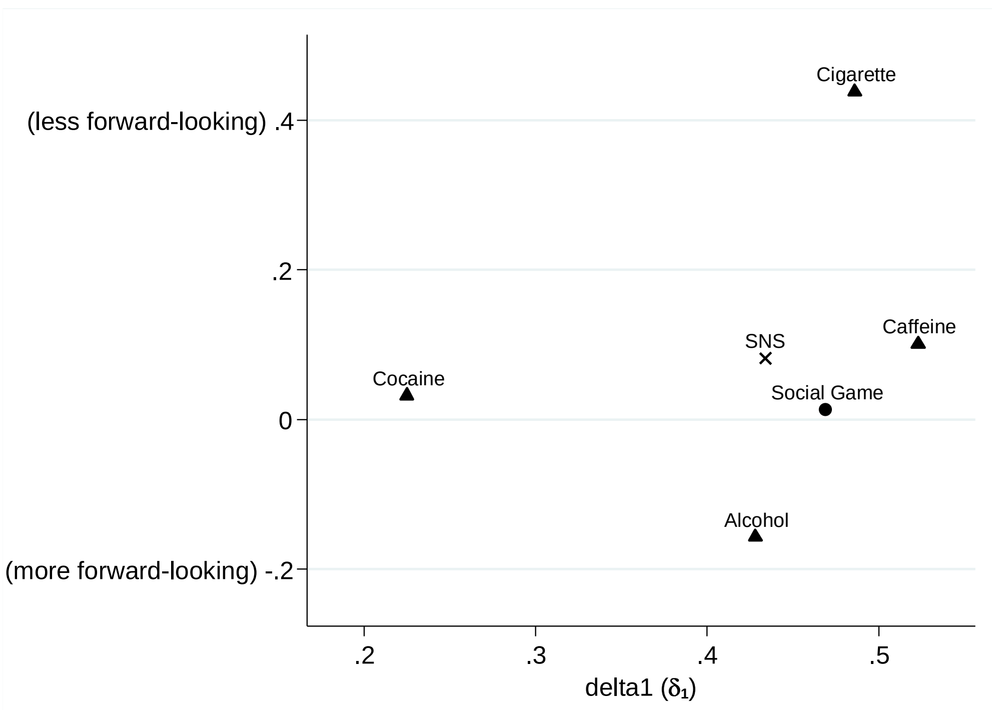


Table 2 **Degree of Reinforcement (δ_1) and Forward-Looking Behavior (r) Across Different Substances**

	SNS	Social Game	Cigarette (Chaloupka 1991)	Caffeine (Olekalns and Bardsley 1996)	Alcohol (Baltagi and Griffin 2002)	Cocaine (Grossmans and Chaloupka 1998)
$\hat{\delta}_1$	0.434***	0.469***	0.486***	0.523***	0.428***	0.225***
$\hat{\delta}_2$	0.401***	0.463***	0.338**	0.475***	0.508***	0.218***
$\hat{\delta}_3$	1.373***	0.470***	-1.671*	-2.887***	-1.986***	-0.008***
r	0.082	0.013	0.438	0.101	-0.157	0.032

*Note: *** p<0.01, ** p<0.05, * p<0.1*

4.5. Subsample Analyses

Addictive behaviors may vary based on demographic factors and user characteristics (Chaloupka 1991). Social influence and latent homophily have been found to significantly affect the behaviors of online users (Ma et al., 2014). To account for the varying degrees of rational addiction to mobile social apps according to user-related factors (e.g., age, education, and income), we performed estimations using separate demand equations for different user groups. Specifically, we divided the sample into two sub-samples according to age (7—29 years and 30—69 years), two different sub-samples according to education (high school graduates and university graduates), and two more sub-samples according to income (≤$3,000/month and >$3,000/month)[3].

Table 3 shows that our main results are robust in light of the sub-sample analyses. Panel 1 shows that addictive behavior in users of SNS is more pronounced in younger and more-educated users than their older and less-educated counterparts. Similar observations were found for high-income user groups. In terms of the rationality of addictive behaviors, we find that addictive behaviors towards SNS are more rational for the younger, high-income groups due to their greater time preference for future (i.e., lower interest rate). Furthermore, rational addicts who are younger, less-educated are more responsive to social liquidity within SNS than other groups. Panel 2 shows that addictive behaviors in users of social games are more pronounced for older, more-educated, and high-income users. In terms of the rationality of addictive

[3] Includes users in the 30-69 age group only.

behaviors, we find that addictive behaviors in users of social games are more rational for older, more-educated, and high-income users. In addition, we find that rational addicts with low incomes are more responsive to social liquidity in their use of social games. Hence, the results of our sub-sample analysis demonstrate that the extent of rational addiction to social apps varies considerably across diverse demographic groups and app categories.

Table 3 Sub-Sample Analyses Results

SNS (Panel 1)	Age		Education		Income	
	7~29	30~69[a, b]	High School Graduated	University Graduated[a, c]	Below $3000[d]	above $3000[a]
VARIABLES	C(t)	C(t)	C(t)	C(t)	C(t)	C(t)
$C_{i,t-1}$, $\hat{\delta}_1$	0.444***	0.382***	0.357***	0.406***	0.298***	0.359***
	(0.0260)	(0.0240)	(0.0321)	(0.0169)	(0.0345)	(0.0271)
$C_{i,t+1}$, $\hat{\delta}_2$	0.420***	0.328***	0.336***	0.349***	0.269***	0.328***
	(0.0113)	(0.0262)	(0.0242)	(0.0181)	(0.0379)	(0.0304)
L_t, $\hat{\delta}_3$	2.122***	0.384**	1.330***	0.480***	1.079***	0.554**
	(0.289)	(0.187)	(0.437)	(0.155)	(0.337)	(0.279)
Interest rate, r	0.0571	0.1646	0.0625	0.1633	0.1078	0.0945
Observations	50,183	54,792	10,029	61,463	10,500	43,065
Number of users	1,189	1,521	268	1,649	294	1,206
Social Game (Panel 2)	**Age**		**Education**		**Income**	
	7~29	30~69	High School Graduated	University Graduated	Below $3000[e]	above $3000
VARIABLES	C(t)	C(t)	C(t)	C(t)	C(t)	C(t)
$C_{i,t-1}$, $\hat{\delta}_1$	0.447***	0.467***	0.444***	0.458***	0.422***	0.464***
	(0.0202)	(0.00916)	(0.0179)	(0.0104)	(0.0224)	(0.00912)
$C_{i,t+1}$, $\hat{\delta}_2$	0.383***	0.465***	0.437***	0.463***	0.410***	0.466***
	(0.0395)	(0.0200)	(0.0183)	(0.0211)	(0.0292)	(0.0207)
L_t, $\hat{\delta}_3$	0.690***	0.575***	0.922***	0.633***	1.208***	0.673***
	(0.254)	(0.202)	(0.336)	(0.216)	(0.315)	(0.235)
Interest rate, r	0.1671	0.0043	0.0160	-0.0108	0.0293	-0.0043
Observations	9,741	40,506	7,609	38,141	9,184	30,721
Number of users	458	1,366	244	1,343	286	1,059

*Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in parentheses. Hansen test of over-identification, and difference-in-Hansen tests of exogeneity of the instrument subset test at the 10% level. We reject the Arellano-Bond test for AR(1) and AR(2), but cannot reject it for AR(3) at the 5% significance level. Hence, our set of instruments is appropriate to the data. For SNS, we use [Ci,t-4,…, Ci,t-41] and [Lt-3,…, Lt-40] and social game app C′i,t-1 as instruments. For the social game, we use [Ci,t-4,…, Ci,t-16] and [Lt-3,…, Lt-15] and SNS app C′i,t-1 as instruments.*

[a] *Cannot be rejected for AR(3) at the 1% significance level*

[b] *Difference-in-Hansen tests of exogeneity of instrument subset test at the 5% level.*

[c] *We use [Ci,t-4,…, Ci,t-41] and [Lt-3,…, Lt-40] and the social game app C′i,t-2 as instruments.*

[d] *We use [Ci,t-3,…, Ci,t-41] and [Lt-2,…, Lt-40] and the social game app C′i,t-1 as instruments.*

[e] *we use [Ci,t-4,…, Ci,t-16] and [Lt-3,…, Lt-15] and SNS app C′i,t-3 as instruments.*

4.6. Rational Addiction and Consumption Volume

Are light users more rational than heavy users? Becker and Murphy (1991) did not address this issue mainly because they relied on aggregate-level sales data. We empirically tested whether heavy users exhibit different addictive patterns than light users by categorizing app users into two groups based on the median usage time (i.e., top 50% vs. bottom 50% in terms of usage). The findings suggest that for both social game and SNS categories, heavy users exhibited stronger addictive propensities (i.e., reinforcement effects) than light users (see Table 4). For social games and SNSs, the coefficients, $\hat{\delta}_1$ and $\hat{\delta}_3$, which represent a users' propensity to addiction and responsiveness to social liquidity, respectively, are more positive for heavy users than for light users. This pattern indicates that heavy users are not only more prone to digital addiction but are more sensitive to changes in social liquidity than light users. Figures 3 and 4 represent the differences between the two groups in response to reinforcements and social liquidity.

Table 4 A Test Against Heavy and Light Users

Application Type	SNS		Social Game	
Consumption Level	Low 50%	High 50%	Low 50% [a]	High 50%
VARIABLES	C(t)	C(t)	C(t)	C(t)
$C_{i,t-1}$, $\hat{\delta}_1$	0.257***	0.442***	0.372***	0.469***
	(0.0217)	(0.0236)	(0.0196)	(0.00867)
$C_{i,t+1}$, $\hat{\delta}_2$	0.224***	0.407***	0.332***	0.459***
	(0.0280)	(0.0115)	(0.0326)	(0.0201)
L_t, $\hat{\delta}_3$	0.192***	2.042***	0.724***	0.806***
	(0.0457)	(0.246)	(0.113)	(0.287)
Interest rate, *r*	0.147321	0.085995	0.120482	0.021786
Average Weekly Consumption (min)	3.262	98.044	16.547	146.418
Observations	45,436	59,539	21,964	28,283
Number of users	1,355	1,355	912	912

*Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in parentheses. Hansen test of over-identification, and difference-in-Hansen tests of exogeneity of the instrument subset test at the 10% level. We reject the Arellano-Bond test for AR(1) and AR(2), but cannot reject it for AR(3) at the 5% significance level. Hence, our set of instruments is appropriate to the data. For SNS, we use [Ci,t-4,…, Ci,t-41] and [Lt-3,…, Lt-40] and social game app C′i,t-1 as instruments. For the social game, we use [Ci,t-4,…, Ci,t-16] and [Lt-3,…, Lt-15] and SNS app C′i,t-1 as instruments. Results remain qualitatively unchanged after excluding both the top and bottom 1% according to their average weekly consumptions.*

[a] *We cannot reject the Arellano-Bond test for AR(3) at the 1% significance level.*

Figure 3 **Degree of Reinforcement (δ_1)**

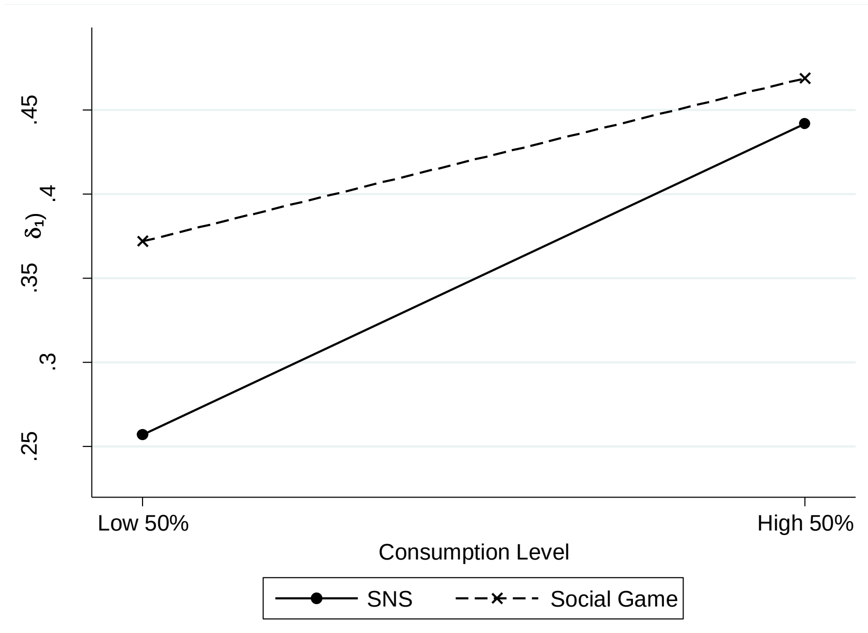
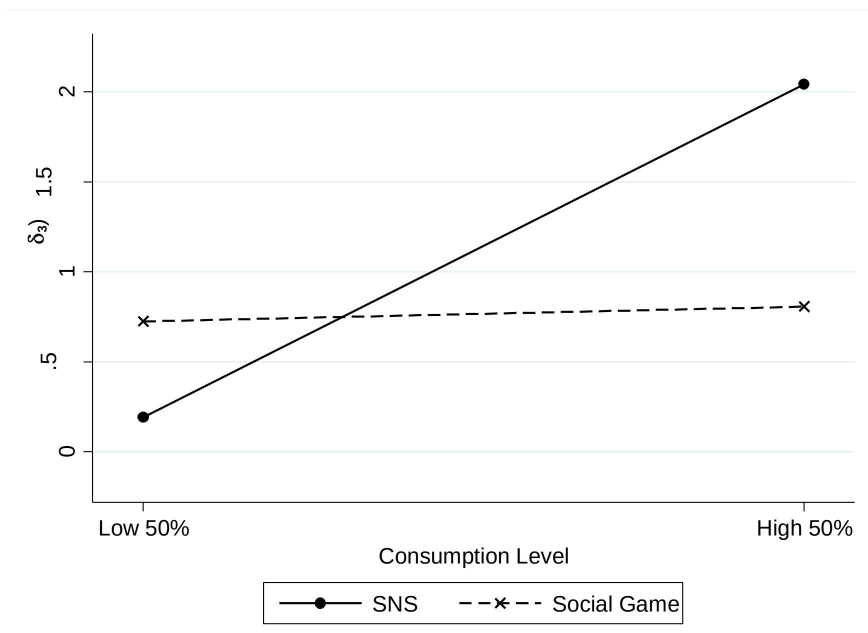


Figure 4 **Susceptibility to Social Liquidity (δ_3)**



Furthermore, rational addictive behaviors are more pronounced in heavy users than light users. The interest rate (r) indicates strong correlation between individuals' propensity for rational addiction and their consumption volume. It should be noted that $r = \hat{\delta}_1/\hat{\delta}_2 - 1$ is negatively associated with rational addiction. Figure 5 suggests that heavy users are more rational than light users for both SNS and social games. This pattern may hint that heavy users more strongly downplay the risk from enhanced tolerance [i.e., the utility from a given amount of consumption is lower (less satisfying) when past consumption is greater] that arises from increased consumption. In other words, heavy users appear to "rationally" ignore the potential hazards of increased addictive stocks as expected benefits outweigh potential costs. Table 5 presents a summary of the key findings.

Figure 5 Forward-Looking Behaviors (r) for Social Apps

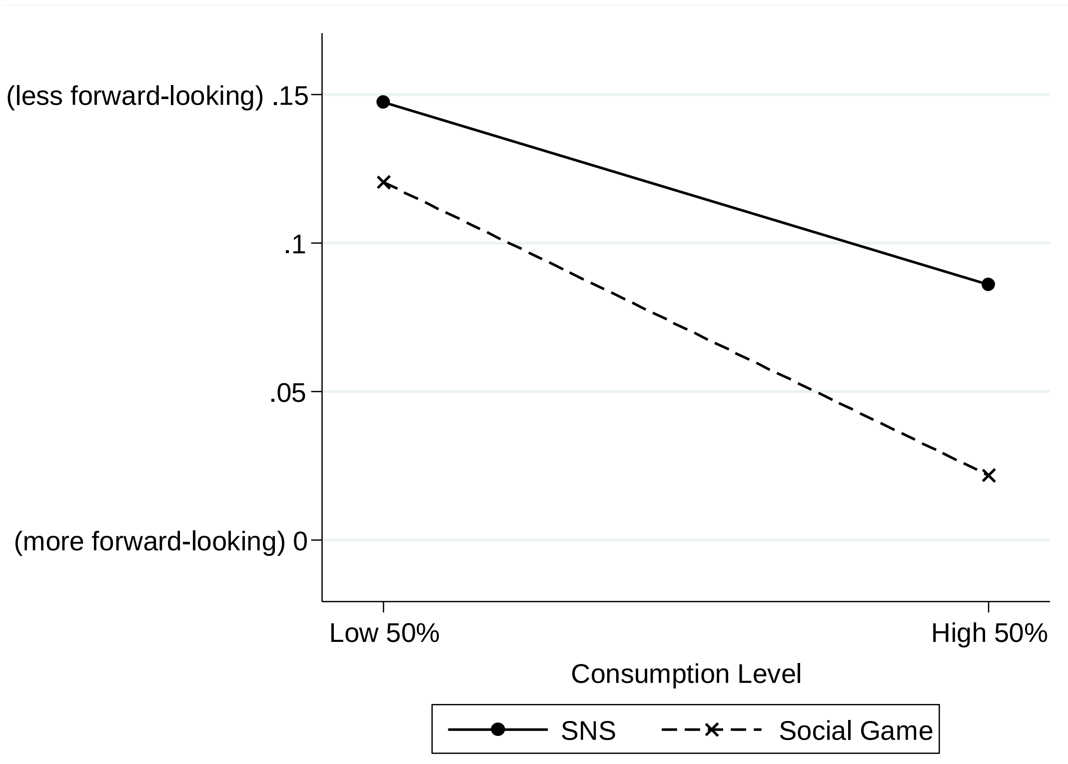


Table 5 A Summary of Key Findings

Rational Addiction Propensity	• Users of mobile social apps exhibit rational addiction behaviors. That is, users of these apps rationally establish inter-temporal consumption structures in order to derive optimal utility. • Compared to the myopic model, which suggests that current consumption depends solely on past consumption, the rational addiction framework strongly demonstrates that current consumption of mobile apps rests on both past and future consumption. • Social liquidity plays a crucial role in regulating the consumption of mobile social apps. • Users of SNS are more sensitive to changes in social liquidity than users of social game.
Physical Addiction vs. Digital Addiction	• Digital substances (e.g., SNS and social games) are as addictive as notoriously habit-forming physical substances (e.g., alcohol, caffeine, and cigarette).
Demographics and Rational Addiction	• Rational addictive behavior of SNS users is more pronounced for younger user groups than older user groups. • In the case of social games, older user groups are more rationally addicted compared to younger user groups. • Highly educated groups are more addicted to SNS, but behave less rationally than less highly educated groups. • Highly educated groups who play social games exhibit more rational addictive behaviors. • Regardless of app type, rational addictive behaviors are more pronounced for high-income groups than low-income groups.
Rational Addiction and Consumption Amount	• For both SNS and social games, heavy users are not only more prone to reinforcement effects, but are more sensitive to changes in social liquidity than light users. • For both SNS and social games, heavy users are more rational than light users

4.7. Robustness Checks

4.7.1. The myopic model of addiction. Because a future consumption term in Equation 13 is derived from the second term of the first-order condition (Equation 11), a significant value for $\hat{\delta}_2$ indicates that each individual carefully considers the impact of current consumption on future utility and future consumption (Becker et al. 1994). However, the myopic model does not incorporate the future utility term in the first-order condition; instead, it only includes past consumption. Therefore, the myopic model is likely to overestimate the impact of past consumption. As expected, Table 6 shows that the myopic model of addiction overestimates the effects of past consumption for both SNS (0.577 > 0.434, p-value <0.01) and social games (0.661 > 0.469, p-value <0.01).

Table 6 GMM Estimates Using the Myopic Model of Addiction

	C(t)	
Variables	SNS Facebook	Social Game Anipang
$C_{i,t-1}$, $\hat{\delta}_1$	0.577***	0.661***
	(0.0418)	(0.0162)
L_t, $\hat{\delta}_3$	2.259***	1.787***
	(0.322)	(0.224)
Observations	107,737	52,156
Number of users	2,762	1,909

*Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in parentheses. For SNS, we use [Ci,t-4,…, Ci,t-41] and [Lt-3,…, Lt-40] and the social game app C′i,t-1 as instruments. For the social game, we use [Ci,t-3,…, Ci,t-26] and [Lt-2,…, Lt-25] and SNS app C′i,t-1 as instruments.*

4.7.2. Forward-looking behavior. Most empirical research on rational addiction relies on the assumption that individuals can forecast future prices accurately. This assumption has been criticized because very few price increases are announced a year in advance (Gruber and Koszegi 2001). To redress this oversight, Gruber and Koszegi (2001) suggested an alternative mechanism for testing forward-looking behaviors using monthly cigarette consumption data. They find that tax increases that are yet to be implemented lead to decreased consumption of cigarettes, which is strong evidence of forward-looking behaviors. In keeping with Gruber and Koszegi (2000)'s approach, we test whether users of social apps exhibit forward-looking behaviors. We consider the following model for a specific event for each social app:

$$C_{i,t} = \alpha + \beta * EVENT_t + \gamma * PreAnnounce_t + \delta * I_i + \phi * T_t + \epsilon \quad (14)$$

where $C_{i,t}$ is the amount of social app consumption by individual *i* at time *t*; $EVENT_t$ is the dummy variable indicating that the event is actually launched at time *t*; $PreAnnounce_t$ is the dummy variable indicating that the event is pre-announced at time *t*; and I_i and T_t are full sets of individual and week dummies, respectively. In this scenario, when an event is pre-announced but not yet implemented, $PreAnnounce_t$

has a value of 1 and $EVENT_t$ has a value of 0. When an event is actually launched, both $EVENT_t$ and $PreAnnounce_t$ have a value of 1. For SNS, we use the launch of "Facebook Home," which provides new features for Facebook app, as an event for Facebook. Similarly, for social game, "Anipang for Sacheonseong," which is the upgrade of Anipang, is considered an external event for Anipang.

Table 7 presents the results of Gruber and Koszegi (2000) test for forward-looking behavior using these two events. The coefficient of $PreAnnounce_t$ is positive and significant for Facebook. Facebook users were found to increase their weekly consumption substantially (i.e., by as much as 651 seconds) when the dominant SNS company pre-announced the launch of its Facebook Home app. This finding provides strong evidence of forward-looking behaviors, at least for this population. In the case of Anipang, the coefficient of $PreAnnounce_t$ is negative and significant. This shows that Anipang users have already reduced their weekly consumption significantly (i.e., as much as by 12,291 seconds) when the top social game provider pre-announced its future launch of a new replacing version. One plausible explanation is that Anipang users forecast that the liquidity of Anipang would decrease when the new version was launched. These results confirm the forward-looking behavior of social app users, which is further strong evidence in favor of the rational addiction model.

Table 7 Effect of Pre-announcement on App Consumption – Fixed Effects Model

	C(t)	
VARIABLES	SNS[a] Facebook	Social Game Anipang
$EVENT_t, \hat{\beta}$	2,717***	-605.4
	(167.4)	(429.1)
$PreAnnounce_t, \hat{\gamma}$	651.0***	-12,291***
	(159.6)	(299.9)
Observations	113,532	56,338
Number of users	2,986	2,182

*Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses. A complete set of time dummy variables is included to account for fixed time effects. Facebook Home was launched on 17 April 2013 and pre-announced on 5 April 2013 in Korea. Anipang for Sacheonseong was launched on 19 February 2013 and pre-announced on 10 January 2013.*

4.7.3. Group-level liquidity. In the absence of individual user-level liquidity information in our data, we conducted robustness checks by restricting liquidity to users with the same demographic profile (i.e., sex, job, education, and income). Specifically, we define *g(i)* as a group of users who share the same demographic profile with user *i*. As such, $L_{g(i),t}$ stands for the liquidity of group *g(i)*, which we use in lieu of L_t in our model. As shown in Table 8, for all *g(i)*s based on sex, job, education, and income, the results remain qualitatively similar to those obtained in the main analysis.

Table 8 Robustness Check Results

SNS (Panel 1)	Group		
	Gender	Education	Income [a]
VARIABLES	C(t)	C(t)	C(t)
$C_{i,t-1}$, $\hat{\delta}_1$	0.435***	0.433***	0.434***
	(0.0267)	(0.0281)	(0.0240)
$C_{i,t+1}$, $\hat{\delta}_2$	0.403***	0.403***	0.394***
	(0.0123)	(0.0132)	(0.0115)
$L_{g(i),t}$, $\hat{\delta}_3$	2.436***	2.246***	3.662***
	(0.309)	(0.299)	(0.434)
Interest rate, *r*	0.0794	0.0744	0.1015
Observations	104,975	104,975	104,975
Number of users	2,710	2,710	2,710
Social Game (Panel 2)	**Group**		
	Gender	Education	Income [b]
VARIABLES	C(t)	C(t)	C(t)
$C_{i,t-1}$, $\hat{\delta}_1$	0.469***	0.468***	0.473***
	(0.00865)	(0.00890)	(0.00935)
$C_{i,t+1}$, $\hat{\delta}_2$	0.464***	0.461***	0.463***
	(0.0197)	(0.0203)	(0.0210)
$L_{g(i),t}$, $\hat{\delta}_3$	0.940***	0.756***	1.159**
	(0.335)	(0.242)	(0.480)
Interest rate, *r*	0.0108	0.0152	0.0216
Observations	50,247	50,247	50,247
Number of users	1,824	1,824	1,824

*Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in parentheses. Hansen test of over-identification, and Difference-in-Hansen tests of exogeneity of our instrument subset test at the 10% level. We reject the Arellano-Bond test for AR(1) and AR(2), but cannot reject it for AR(3) at the 5% significance level. Hence, our set of instruments is appropriate to the data. For SNS, we use [Ci,t-4,…, Ci,t-41] and [Lg(i),t-3,…, Lg(i),t-40] and social game app C′i,t-1 as instruments. For the social game, we use [Ci,t-4,…, Ci,t-16] and [Lg(i)t-3,…, Lg(i)t-15] and SNS app C′i,t-1 as instruments.*

[a] *We use [Ci,t-3,…, Ci,t-41] and [Lg(i)t-2,…, Lg(i)t-40] and the social game app C′i,t-1 as instruments.*

[b] *We use [Ci,t-4,…, Ci,t-13] and [Lg(i)t-3,…, Lg(i)t-12] and SNS app C′i,t-1 as instruments.*

4.8. Falsification Tests Results

Auld and Grootendorst (2004) demonstrated that the rational addiction model tends to yield spurious evidence in favor of the rational addiction hypothesis even for non-addictive goods, such as milk, eggs, oranges, and apples, especially when aggregate data are used. Note that we do not use aggregate data, but individual user-level data to estimate the rational addiction model in this study. Nevertheless, to address the issue of the potential spurious relations, we conducted falsification tests. To disprove alternative explanations such as, for example, mobile apps are generally addictive. Specifically, we considered popular smartphone "utility apps" that are regarded as non-socially addictive, such as the camera, photo gallery, and address book. If these apps are not germane to rational addiction theory, our results in favor of the rational addiction hypothesis will be further strengthened. Table 9 shows the results of the falsification tests. No significant impact of future or past consumption is evident (95% confidence level). Apps, such as the camera, photo gallery, and address book, are neither addictive, nor rational. Consequently, we can successfully reject the falsification argument and assert the rigor of our rational addiction framework in this context.

Table 9 GMM Estimates of the Rational Addiction Model using Non-addictive Apps

	C(t)		
Variables	Camera	Gallery	Address Book
$C_{i,t-1}$, $\hat{\delta}_1$	0.174*	-0.0314	0.212
	(0.105)	(0.185)	(0.185)
$C_{i,t+1}$, $\hat{\delta}_2$	0.0241	-0.0301	0.0961
	(0.0772)	(0.370)	(0.313)
L_t, $\hat{\delta}_3$	1.676***	-1.243	-0.143
	(0.196)	(0.945)	(0.366)
Observations	9,923	9,620	12,139
Number of users	2,426	2,311	2,704

*Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in parentheses. We collected data between March 5, 2012 and April 29, 2012 (8 weeks) for the falsification test. For the camera, we use [Ci,t-3,…, Ci,t-8] and [Lt-2,…, Lt-7] and SNS app C′i,t-1 as instruments. For the gallery, we use [Ci,t-4,…, Ci,t-8] and [Lt-3,…, Lt-7] and SNS app C′i,t-1 as instruments. For the address book, we use [Ci,t-3,…, Ci,t-8] and [Lt-2,…, Lt-7] and SNS app C′i,t-1 as instruments.*

5. Discussion and Implications

5.1. Rational Addiction to Social Apps

Our findings lend credence to the notion of rational addiction in the context of mobile social app consumption. Rational addiction to social games and SNS can be interpreted as an indication that the users of these social goods are in control of their thinking and actions when confronted with consumption decisions. Self-regulation is widely recognized as a key component of rationality with which one can maximize his or her own utility. In this light, rational addicts can be regarded as ostensibly less susceptible to health risks than are myopic addicts because of their ability for self-control.

Caution must be used, however, when interpreting the idea of "rationality." An issue worth noting is that consuming addictive substances "rationally," as enabled by self-regulation, does not necessarily mean consuming less of such goods or being immune to addiction. Being "rational" simply means attempting to maximize utility consistently over time given constraints and therefore exerts no direct implications for consumption quantity (Becker and Murphy, 1988). In certain situations, rational addicts can consume a greater amount of addictive substances if doing so translates to utility maximization. For example, when rational addicts anticipate that more users will adopt particular social games or SNS platforms in the future, they will extend efforts to increase their current consumption of such goods to maximize utility. By contrast, myopic addicts neither anticipate nor weigh future consequences (Becker and Murphy, 1988).

These observations lead us to argue that in certain environments, rational addicts could be more susceptible to negative health consequences (e.g., depression, somatic symptoms, and aggression) than are myopic addicts. Furthermore, rational addicts often experience more difficulty in overcoming addiction than do myopic addicts. Becker and Murphy (1988) assert that rational addicts may deliberately postpone terminating their addiction as they attempt to find ways to optimally minimize short-run loss of utility from abruptly ceasing consumption. For example, rational smoking addicts initially endeavor to stop smoking by experimenting with easier aids (e.g., substituting gum chewing or jogging for smoking) until they find the "best" method for quitting smoking with minimum short-term loss of utility. That is, all factors being equal, rational addicts may be confronted with more failures when attempting to terminate addiction given that they are more "fastidious" than myopic addicts in determining an optimal quitting method. The aphorism, "ignorance is always bold; knowledge hesitates," seems to be an apt description of the potential hazards of rational addiction.

5.2. Variations in Addiction Vulnerability

The findings provide initial insight into the nature and state of variations in addiction vulnerability. Individuals substantially differ in terms of rational capability (Becker and Murphy 1988), which suggests that addiction propensity also varies contingent on contextual factors. The structure of inter-temporal consumption demand reveals that individuals become more vulnerable to digital addiction under the following conditions. First, given that positive reinforcement drives the development of an addictive behavior, individuals who are exposed to stronger positive reinforcement and exhibit resilient consumption inertia are more susceptible to digital addiction. Second, the more sensitive an individual is to social liquidity or network effects, the greater his or her vulnerability to digital addiction. More vulnerable addicts will proactively increase their current consumption of apps when they expect future social liquidity or network effects to increase. Third, less forward-looking individuals who heavily discount the exacerbating effects of current consumption on future harmful consequences are more vulnerable to addiction. These addicts tend to appraise the utility gained from consuming social apps as outweighing the discounted reduction in utility arising from adverse consequences.

Variations in addiction vulnerability exist across diverse demographic clusters and app characteristics. In the case of SNS, users who are older and more educated are less-forward-looking and are therefore more vulnerable to addiction. By contrast, exactly the opposite holds true for social games; that is, younger and less educated users are less forward-looking. Although further inquiry is necessary, this dissimilarity in results between the two app categories can be partly attributed to differences in the inherent utility each category is perceived to offer. Older and more educated users may too highly appraise the utility accrued from the positive use of SNS, thereby becoming less rational in managing the inter-temporal consumption of such sites. Contrastingly, these demographic groups tend to relatively undervalue the intrinsic utility derived from playing social games and therefore more effectively manage inter-temporal consumption.

5.3. Implications for Practice and Policy-Making

Regulatory agencies and lawmakers have become increasingly concerned with the addictive qualities of SNS and platform games, treating their usage as a growing social pandemic affecting many lives, especially those of young, "vulnerable" people. In fact, these social apps may have already become pastimes for adolescents with narcissistic tendencies who, many experts believe, are likely to experience the adverse consequences of the mental escapism, procrastination, preoccupation, and poor time-management that so often accompany addictive behaviors; suicide may even be one of these consequences (Kuss and Griffiths, 2011).

To address this issue, government agencies have taken preventative steps, but only in a regulatory and coercive way. For example, since 2010, Korea's Ministry of Culture, Sports, and Tourism has implemented a new controversial law, dubbed the "Cinderella Law," that forbids game providers from offering services to teenagers under 16, between midnight and 6 a.m. Similarly, the Vietnamese government has adopted curfews that automatically block access to online games at night and early in the morning. China's Ministry of Culture has issued a mandate forcing online game producers to exclude addictive features in online games, such as gambling and pornography. In addition, underage players are not allowed to use online game currencies created by game developers. In Europe and the United States, all online games are strictly rated by regulatory boards (e.g., PEGI in Europe and the ESRB in the US.). These rating schemes are obviously intended to prevent addictions to pervasive game content, especially among adolescents. When regulation has no or little effect, concerned parents may use punishment or send their children to clinics or specialized experts to cure their addiction to SNS or games.

Guidelines, regulations, and policies have only been temporarily successful, in limited ways in curbing addiction. Their effectiveness has been extensively questioned due to their many obvious legal loopholes and dodges. The U.S. Supreme Court has recently overturned a California state law banning the sale of certain video game products to minors because the rule at stake violates free-speech rights.[4] In Korea, the "Cinderella Law" of 2011 has been ineffective; teenagers simply use their parents' login information to play games during lockdown periods.[5]

Our findings suggest that individuals' internal self-regulation based on rationality may be the best form of regulation to effectively cope with "app-dictions." According to the data analyzed, although variations exist across diverse demographic groups, users of social apps embedded in smartphones are indeed rational in that they manage their current consumption to maximize their utility. Social liquidity plays an important role in the distribution of users' app consumption across temporal spaces. To enhance the rationality of smartphone consumers further and prevent them from crossing the line into uncontrollable addiction, developers of social apps should design additional usability features that aid users to identify the degree of social liquidity easily. Currently, financial markets offer investors current information on the state of market liquidity on a real-time basis (e.g., the number of trades), which helps them to project ahead of time the optimal timing and strategies for trading. Users of social apps may benefit from similar signaling add-ons to plan the distribution of their consumption of social apps, manage their usage wisely, and maximize utility. For example, some social games, such as Anipang in Korea, currently publish a leader scoreboard, which lists who has the highest points among a user's circle of friends connected through a platform. To promote more social exchanges, the scoreboard is constantly updated for a player's SNS contacts. In addition to scoreboards, developers could also openly disseminate usage metrics to inform players about how intensively their contacts are participating. Users of social apps exhibit different consumption patterns when new rules are enacted (Claussen et al., 2013). These liquidity posts can help users learn about and predict the usage patterns of their friends more accurately and manage their own inter-temporal consumption wisely to gain optimal utility.

[4] http://www.washingtonpost.com/politics/supreme-court-strikes-calif-law-banning-sale-of-violent-video-games-to-minors/2011/06/26/AGwtxenH_story.html

[5] http://www.techspot.com/news/46867-korea-bans-kids-from-late-night-gaming-they-dont-listen.html

5.4 Implications for Research

The rational addiction framework has been applied in diverse contexts to investigate various addictive behaviors. Nevertheless, most empirical studies have been limited to physical commodities, such as alcohol, cigarettes, and drugs, which cost money to consume. Our alterations and enrichment of the theoretical basis provided by Becker and Murphy (1988) can offer a fresh vantage point from which to study digital addictive behaviors involving non-physical, non-monetary, and highly social commodities.

The emerging phenomenon of rational addiction to social apps was scrutinized in a nuanced, empirical analysis of how individual user characteristics influence addictive behaviors. While previous studies into patterns of rational addiction have offered holistic insights based on the analysis of aggregated sales data with no reference to individual characteristics, our individual level and comprehensive panel data enabled us to observe notable differences across diverse user groups. For example, the individual-level consumption data allowed us to examine the dynamics of the relationship between the propensity for rational addiction and the amount consumed. It is noteworthy that rationality or self-regulation does not necessarily translate into the consumption of less addictive goods, particularly when such commodities are non-physical, highly accessible, and social. In certain situations, a rational addict could be viewed as a "rational fool" who acts consistently but with a narrow spectrum of choices (Sen 1977). Addiction researchers, particularly those who study digital dependency, should not be firmly obsessed with the illusion of "rationality." Rather, they should understand the fact that rational addicts can be exposed to great risk due to their consistent planned actions to maximize utility.

6. Limitations and Future Research

Several limitations of this study along with directions for future research need to be noted. Our findings are derived based primarily on an analysis of the two most representative social apps, and, therefore, we make no attempts to generalize our results to other social apps. Furthermore, major SNS sites, such as Facebook, Twitter, and Linkedin, differ substantially in terms of value propositions, business scope, and target customers, as well as available socialization features and functionalities. These structural heterogeneities inherent to diverse SNS sites may influence users' future orientation and app consumption patterns. Future research should be directed toward determining if these differences influence the findings reported in this study.

Another caveat is related to the model specification. Consistent with Becker et al. (1994), our model prioritizes parsimony and substantive importance over predictive power and policy counterfactuals. Consequently, we may have omitted several control variables from our specifications. For example, apart from social liquidity, other factors (e.g., platform type, price, reward systems) may affect social apps consumption. Although our model competently explains a large portion of variances in observed consumption regularities, we acknowledge the model's parsimony as a limitation. Future studies could expand the menu of variables to enhance the model's richness and comprehensiveness. Furthermore, the reduced-form approaches used to implement our model estimation prevents us from examining alternative policies. Gordon and Sun (2015) recently developed a structural model of addiction and stockpiling to examine cigarette consumption. Future research can benefit from the comprehensive empirical insights that may be revealed by the structural estimation approach.

Finally, the mobile paradigm is rapidly altering the dynamics of users' socialization process and communication protocols. Although the empirical scrutiny of 13-month long, weekly panel data may suffice to understand users' behaviors, the unprecedented pace of the mobile revolution and the perpetual flux in the demand structures for technology suggest that nothing is stable and permanent, including the way we rationalize and justify our online behaviors. Therefore, a more nuanced and systematical inquiry is clearly needed into the continuous interplay between human rationality and technology evolution.

7. Conclusion

The pervasive penetration of mobile devices into everyday life has made it more difficult than ever to resist social exchanges over mobile apps. On the one hand, mobile platforms and apps have been touted as a boon to social connectivity within or across one's interpersonal boundaries. On the other hand, the excessive use of and compulsive dependence on mobile IT artifacts have become major social problems around the globe.

The benefits from social apps appear to be overshadowed by addiction-related challenges. Mobile devices are particularly facilitative of addictive behavior because of their easy accessibility and portability. A medical doctor who specializes in digital addiction warns that “convenience is the mother of addiction” and highlights the need for a “digital diet.” Fixation with digital platforms can be as detrimental as physical addiction, such as dependence on alcohols and drugs.

This study extended Becker and Murphy’s (1988) rational addiction framework to determine whether the fundamental economic principle of utility-maximization and rational behavior directs consumption patterns for highly addictive social apps, such as SNS and social games. The findings based on comprehensive panel data on weekly app consumption provide full support for the rational addiction paradigm. To maximize the discount utility of social apps, the users of these apps amplify their sensitivity to social liquidity as they build their inter-temporal consumption structures. These app users are rational in that they effectively adjust consumption over time horizons to derive optimal utility. Although our results provide insight into decision making and behavior among rational addicts, the findings cannot be interpreted as evidence that users’ “app-diction” problems are insignificant or that such problems easily lend themselves to tolerance. In fact, our results strongly confirm that heavy users are not only more prone to rational addiction, but are also more sensitive to changes in social liquidity. In certain situations, rational addicts are at a greater risk than myopic addicts because the former can be impressionable; that is, they are easily encouraged to heavily consume digital substances up-front in pursuit of optimal utility.

As mobile technology advances and increases in pervasiveness, vulnerability to digital addiction will only increase immensely, thereby taking a potentially tremendous toll on public health. The advent of new, user-friendly digital technologies, such as wearables and sensing devices, may significantly exacerbate digital addiction. IT professionals and businesses continue to enhance the on-demand experience of users with technologies. Yet, ubiquity and advancement come with a price. Researchers must be mindful of the dynamic interplay between technological innovation and human behaviors given technology’s apparent tendency to exceed our rational capability to manage our consumption of innovations.

References

Arellano, M., and Bond, S. 1991. "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations." *The Review of Economic Studies* (58:2), pp. 277-297.

Auld, C., and Grootendorst, P. 2004. "An empirical analysis of milk addiction." *Journal of Health Economics* (23:6), pp. 1117-1133.

Baltagi, B., and Griffin, J. 2002. "Rational addiction to alcohol: panel data analysis of liquor consumption." *Health Economics* (11:6), pp. 485-491.

Baumeister, R., and Leary, M. 1995. "The need to belong: desire for interpersonal attachments as a fundamental human motivation." *Psychological Bulletin* (117:3), pp. 497-529.

Becker, G., Grossman, M., and Murphy, K. 1994. "An empirical analysis of cigarette addiction." *American Economic Review* (84:3), pp. 396-418.

Becker, G., and Murphy, K. 1988. "A theory of rational addiction." *Journal of Political Economy* (96:4), pp. 675-700.

Becker, G., Grossman, M., and Murphy, K. 1991. "Economics of Drugs: Rational Addiction and the Effect of Price on Consumption," *American Economic Review* (81:2), pp. 237-241.

Blaszczynski, A., and Nower, L. 2002. "A Pathways Model of Problem and Pathological Gambling," *Addiction* (97:5), pp. 487-499.

Bianchi, A., and Phillips, J.G. 2005. "Psychological Predictors of Problem Mobile Phone Use," *CyberPsychology & Behavior* (8:1), pp. 39-51.

Calvert, R. 1985. "The value of biased information: A rational choice model of political advice." *Journal of Politics* (47:2), pp. 530-555.

Chaloupka, F. 1991. "Rational addictive behavior and cigarette smoking." *Journal of Political Economy* (99:4), pp. 722-742.

Choliz, M. 2010. "Mobile Phone Addiction: A Point of Issue," *Addiction* (105:2), pp. 373-374.

Claussen, J., Kretschmer, T., and Mayrhofer, P. 2013. "The effects of rewarding user engagement: the case of facebook apps." *Information Systems Research* (24:1), pp. 186-200.

Everitt, B.J., and Robbins, T.W. 2005. "Neural Systems of Reinforcement for Drug Addiction: From Actions to Habits to Compulsion," *Nature Neuroscience* (8:11), pp. 1481-1489.

Fang, X., Hu, P., Li, Z., and Tsai, W. 2013. "Predicting adoption probabilities in social networks." *Information Systems Research* (24:1), pp. 128-145.

Fowler, F.J. 1992. "How Unclear Terms Affect Survey Data," *Public Opinion Quarterly* (56:2), pp. 218-231.

Freud, S., Bonaparte, M., and Nathan, M. 1930. "Le mot d'esprit et ses rapports avec l'inconscient." Gallimard Paris.

Gordon, B. and Sun, B. 2015. “A Dynamic Model of Rational Addiction: Evaluating Cigarette Taxes,” *Marketing Science, Forthcoming*

Griffiths, M. 2000. "Internet Addiction-Time to Be Taken Seriously?," *Addiction Research & Theory* (8:5), pp. 413-418.

Grossman, M., and Chaloupka, F. 1998. "The demand for cocaine by young adults: a rational addiction approach." *Journal of Health Economics* (17:4), pp. 427-474.

Gruber, J., and Koszegi, B. 2001. "Is addiction "rational"? Theory and evidence." *Quarterly Journal of Economics* (116:4), pp. 1261-1303.

Herz, A. 1997. "Endogenous Opioid Systems and Alcohol Addiction," *Psychopharmacology* (129:2), pp. 99-111.

Homans, G. 1958. "Social behavior as exchange." *American Journal of Sociology* (63:6), pp. 597-606.

Iannaccone, P. 1984. "Long-term effects of exposure to methylnitrosourea on blastocysts following transfer to surrogate female mice." *Cancer Research* (44:7), pp. 2785-2789.

Igarashi, T., Motoyoshi, T., Takai, J., and Yoshida, T. 2008. "No Mobile, No Life: Self-Perception and Text-Message Dependency among Japanese High School Students," *Computers in Human Behavior* (24:5), pp. 2311-2324.

Katz, M.L., and Shapiro, C. 1985. "Network Externalities, Competition, and Compatibility," *American Economic Review* (75:3), pp. 424-440.

Khalaf, S. 2013. "Flurry five-year report: It's an app world. The web just lives in it." http://www.flurry.com/bid/95723/Flurry-Five-Year-Report-It-s-an-App-World-The-Web-Just-Lives-in-It#.U1-CicuKCUk

Kim, E.J., Namkoong, K., Ku, T., and Kim, S.J. 2008. "The Relationship between Online Game Addiction and Aggression, Self-Control and Narcissistic Personality Traits," *European Psychiatry* (23:3), pp. 212-218.

King, A.L.S., Valença, A.M., and Nardi, A.E. 2010. "Nomophobia: The Mobile Phone in Panic Disorder with Agoraphobia: Reducing Phobias or Worsening of Dependence?," *Cognitive and Behavioral neurology* (23:1), pp. 52-54.

Kuss, D., and Griffiths, M. 2011. "Online social networking and addiction—a review of the psychological literature." *International Journal of Environmental Research and Public Health* (8:9), pp. 3528-3552.

Liu, J., Liu, J., Hammitt, J., and Chou, S. 1999. "The price elasticity of opium in Taiwan, 1914–1942." *Journal of Health Economics* (18: 6), pp. 795-810.

Ma, L., Krishnan, R., and Montgomery, A. 2014. “Latent homophily or social influence? An empirical analysis of purchase within a social network,” *Management Science*, Articles in advance 2014, http://dx.doi.org/10.1287/mnsc.2014.1928

Mobilia, P. 1993. "Gambling as a rational addiction." *Journal of Gambling Studies* (9: 2), pp. 121-151.

Morris, M., and Ogan, C. 1996. "The Internet as Mass Medium," *Journal of Communication* (46:1), pp. 39-50.

Naqvi, N.H., Rudrauf, D., Damasio, H., and Bechara, A. 2007. "Damage to the Insula Disrupts Addiction to Cigarette Smoking," *Science* (315:5811), pp. 531-534.

Olekalns, N., and Bardsley, P. 1996. "Rational addiction to caffeine: an analysis of coffee consumption." *Journal of Political Economy* (104:5), pp. 1100-1104.

Pagano, M. 1989. "Trading volume and asset liquidity." *Quarterly Journal of Economics* (104:2), pp. 255-274.

Peele, S. 1985. *The Meaning of Addiction, Compulsive Experience and Its Interpretation*. Lexington, M.A.: Lexington Books, D.C. Heath and Company.

Pollak, R. 1970. "Habit formation and dynamic demand functions." *Journal of Political Economy* (78: 4), pp. 745-763.

Pollak, R. 1976. "Habit formation and long-run utility functions." *Journal of Economic Theory* (13:2), pp. 272-297.

Roll, R., Schwartz, E., and Subrahmanyam, A. 2009. "Options trading activity and firm valuation." *Journal of Financial Economics* (94:3), pp. 345-360.

Rothberg, M.B., Arora, A., Hermann, J., Kleppel, R., Marie, P.S., and Visintainer, P. 2010. "Phantom Vibration Syndrome among Medical Staff," BMJ: British Medical Journal (Overseas & Retired Doctors Edition) (341:7786).

Ryder Jr, H., and Heal, G. 1973. "Optimal growth with intertemporally dependent preferences." *Review of Economic Studies* (40:1), pp. 1-31.

Sen, A.K. 1977. "Rational Fools: A Critique of the Behavioral Foundations of Economic Theory," *Philosophy and Public Affairs* (6:4), pp. 317-344.

Starr, M. 2014. "Are you addicted to your smartphone?" http://www.cnet.com.au/are-you-addicted-to-your-smartphone-339346504.htm.

Stigler, G., and Becker, G. 1977. "De gustibus non est disputandum." *American Economic Review* (67:2), pp. 76-90.

Stone, M. 2014. "Smartphone Addiction Now Has A Clinical Name." http://www.businessinsider.com/what-is-nomophobia-2014-7

Susarla, A., Oh, J.-H., and Tan, Y. 2012. "Social Networks and the Diffusion of User-Generated Content: Evidence from Youtube," *Information Systems Research* (23:1), pp. 23-41.

Thibodeau, P. 2012. "Cellphone vibration syndrome and other signs of tech addiction." http://www.computerworld.com/article/2504472/smartphones/cellphone-vibration-syndrome-and-other-signs-of-tech-addiction.html?page=3

Turel, O., Serenko, A., and Giles, P. 2011. "Integrating technology addiction and use: An empirical investigation of online auction users." *MIS Quarterly* (35:4), pp. 1043-1061.

Yaari, M. 1977. "Consistent utilization of an exhaustible resource, or, how to eat an appetite-arousing cake." *Center for Research in Mathematical Economics and Game Theory Research memorandum* (26).

Young, K.S. 1998. Caught in the Net: How to Recognize the Signs of Internet Addiction and a Winning Strategy for Recovery. John Wiley & Sons.

Zeng, X., and Wei, L. 2013. "Social Ties and User Content Generation: Evidence from Flickr," *Information Systems Research* (24:1), pp. 71-87.