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Predictors and patterns of problematic Internet game use using a decision tree model

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Background and aims: Problematic Internet game use is an important social issue that increases social expenditures for both individuals and nations. This study identified predictors and patterns of problematic Internet game use. *Methods:* Data were collected from online surveys between November 26 and December 26, 2014. We identified 3,881 Internet game users from a total of 5,003 respondents. A total of 511 participants were assigned to the problematic Internet game user group according to the *Diagnostic and Statistical Manual of Mental Disorders* Internet gaming disorder criteria. From the remaining 3,370 participants, we used propensity score matching to develop a normal comparison group of 511 participants. In all, 1,022 participants were analyzed using the chi-square automatic interaction detector (CHAID) algorithm. *Results:* According to the CHAID algorithm, six important predictors were found: gaming costs (50%), average weekday gaming time (23%), offline Internet gaming community meeting attendance (13%), average weekend and holiday gaming time (7%), marital status (4%), and self-perceptions of addiction to Internet game use (3%). In addition, three patterns out of six classification rules were explored: cost-consuming, socializing, and solitary gamers. *Conclusion:* This study provides direction for future work on the screening of problematic Internet game use in adults.

Keywords: problematic Internet game use, predictors, pattern, decision tree analysis, chi-square automatic interaction detector

INTRODUCTION

As the usage of Internet increases, the number of Internet game players over traditional video game players is increasing. Consistent with this transition, the *Diagnostic and Statistical Manual of Mental Disorders* (DSM-5; Section III, fifth edition) has proposed the criteria for Internet gaming disorder (IGD) (American Psychiatric Association, 2012). Although many issues in the definition of IGD remain to be addressed, the DSM-5 has proposed that IGD is characterized by the persistent and recurrent use of the Internet to engage in games, leading to significant impairment or distress (Holden, 2010).

Recent research has shown that problematic Internet game use is related to diverse neuropsychological and behavioral outcomes, including sleep abnormalities; decreased psychosocial well-being; relationship difficulties; inattention; decreased academic achievement; problems with work, education, and socializing; declining verbal memory performance; maladaptive cognitions; dissociation; aggressive or oppositional behavior; hostility; increased thoughts of committing suicide; and seizures (Allison, von Wahlde, Shockley, & Gabbard, 2006; Batthyány, Müller, Benker, & Wölfling, 2009; Chan & Rabinowitz, 2006; Chuang, 2006; Dworak, Schierl, Bruns, & Strüder, 2007; Hussain & Griffiths, 2009a, 2009b; Jeong & Kim, 2011; Kim & Kim, 2010; Lemmens, Valkenburg, & Peter, 2011; Liu & Peng, 2009; Rehbein, Kleimann, & Mössle, 2010).

Moreover, problematic Internet game use increases the social expenditure for both individuals and nations. Problematic Internet use resulted in academic failure and reduced work performance (Bu & Skutle, 2013), which was followed by detriment to a job or educational career (Kardefelt-Winther,

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2014). Therefore, problematic Internet game use is an important social problem that requires a solution.

To prevent and develop solutions for this problem, studies aimed at understanding the predictive factors and patterns of problematic Internet gaming are needed. Previous studies have shown that male gender, depression, anxiety, alcohol use, smoking, and smartphone use were predictors of problematic Internet use (Chang, Chiu, Lee, Chen, & Miao, 2014; Choi et al., 2015; Floros, Siomos, Stogiannidou, Giouzepas, & Garyfallos, 2014; Heo, Oh, Subramanian, Kim, & Kawachi, 2014; Ho et al., 2014). However, these findings were restricted to demographic or psychological factors and did not consider Internet game styles and patterns. A previous study found that engagement in specific game genres, such as massively multiplayer online role-playing games (MMORPGs), is related to an enhanced risk for problematic Internet game use (Morrison & Gore, 2010). Young (1999) recommended that the clinicians should assess the extent of use among particular application in problematic Internet users. Similarly, in pathological gambling, the extent of gambling pathology would be related to gambling styles and patterns, including frequency of gambling, number of different types of gambling, and specific forms of gambling, such as pull tabs and casino gambling (Welte, Barnes, Wieczorek, Tidwell, & Parker, 2004).

Nevertheless, there is little evidence on the risk factors related to game styles and patterns for problematic Internet game use. Although previous studies attempted to identify the predictive factors based on several methods such as in-depth, psychiatric interviews and content analyses (Allison et al., 2006; Chappell, Eatough, Davies, & Griffiths, 2006; Wan & Chiou, 2006), there were several limitations in terms of methods. Decision tree analysis models are effective at finding the predictive factors and classifying the patterns of problematic Internet game use because decision trees are generated by algorithms that demonstrate various ways of splitting a data set into branch-like divisions (de Ville, 2006). The decision tree is grounded in inductive statistics and splits a complex decision into several simpler decisions. Accordingly, this approach can provide solutions that are easy to interpret (Xu, Watanachaturaporn, Varshney, & Arora, 2005). Thus, decision tree analysis models have been used in the context of nicotine addiction and other healthcare areas. D'Alisa et al. (2006) used the decision tree method to evaluate quality of life related to depression. Mann et al. (2008) created an anticipating model for suicide attempts. Batterham, Christensen, and Mackinnon (2009) asserted that the decision tree method was very useful in predicting risk factors for depressive disorders. Moon, Kang, Jitpitaklert, and Kim (2012) also used the decision tree to find characterizing smoking patterns in older adults. Jackson (2000) employed the decision tree method to identify risk factors for cardiovascular disease and provided guidelines for medical professionals by forecasting the causal risk factors of patients. Schmitz, Kugler, and Rollnik (2003) utilized the decision tree method to predict neuroticism levels. Hummel, Strehmel, Selbig, Walther, and Kopka (2010) predicted the substructure of metabolites using a decision tree profile obtained from gas chromatography mass spectrometry. Although decision tree analysis models have been used in several healthcare fields, there is little research on problematic Internet game use using decision tree analysis.

Therefore, this study aimed to identify the predictive factors including characteristics of game styles and the patterns of problematic Internet game use using the decision tree method, chi-square automatic interaction detector (CHAID) algorithm.

METHODS

Participants

We collected data from a total of 5,003 (2,653 male and 2,350 female) respondents who were recruited through an online research survey company (Hankook Research, Inc.) between November 26 and December 26, 2014. Online informed consent was obtained from all participants, prior to their participation. Participants were native Koreans aged 20–49 years, from metropolitan areas in South Korea. The survey comprised questions on demographic and Internet gaming style characteristics of the participants. The gaming style factors included items, such as maximum gaming time, favorite game style, and gaming costs, which experts deemed important for problematic Internet game use. The experts included psychiatrists, psychologists, and data scientists of medical informatics. Questions related to cost, gaming time, and age were self-reported questions, free text which yielded a continuous value. The rest were multiple-choice questions based on predefined categories.

In all, 3,881 Internet game users were identified, and among them, 511 participants (307 male and 204 female, 13.2% of Internet game users) who answered "yes" to at least five of the nine items of the IGD criteria were assigned to the problematic Internet game user group. From the remaining 3,370 participants, we assigned 511 (302 male and 209 female) to a normal comparison group using propensity score matching (PSM). PSM is used when respondents are not randomly allocated and biased to the experimental or control group in observational studies. The propensity score is defined as the probability that a patient received the experimental intervention conditional on pre-treatment characteristics at baseline (Heinze & Jüni, 2011). PSM has been used to make causal inferences in randomized clinical trials, as well as in non-experimental and observational data (Guo & Fraser, 2009). This method was previously used to account for weaknesses in quasi-experimental designs as it matches individuals in a treatment group to other individuals with comparable characteristics (Peikes, Moreno, & Orzol, 2008). PSM was used in this study to find individuals with characteristics comparable to those of individuals in the problematic Internet user group. The PSM method matched one to one and used the following seven variables as covariates: age, gender, residence, job, academic background, economic level, and marital condition. This resulted in a total sample size of 1,022 participants.

Measures and procedure

This study used the CHAID algorithm for decision tree analysis, which is based upon adjusted significance testing.

This algorithm is advantageous owing to a prediction method similar to regression analysis in addition to classification of patterns. It is particularly useful when the data are not appropriate for regression analyses because the normality assumptions are violated (Murphy & Comiskey, 2013). Another advantage is that it visualizes the relationship between the target (dependent) variable and the related factors in the form of a tree image, which is easy to interpret (Pradhan, 2013).

The first step of decision tree mining is feature selection, which is to select the variables with the strongest effect among all the variables. The importance of all variables is calculated for ranking decisions. This is essential to improve modeling efficiency, performance, and results because unimportant variables are not included in the learning stage. The next step is to separate sample data into training data and validation data to ensure model accuracy. Training data (or training set) refers to that portion of the data used to fit a model. Test data (or test set) refers to that portion of the data used only at the end of the model in building and selection process to assess how well the final model might perform on additional data. First, through data mining, data are trained to fit a model. Then, the final model is developed using trained data.

The research procedure was as follows: 14 variables from an initial 22 variables were selected using feature selection nodes, based on the *p*-value of Pearson's categorical prediction. First, this node indicated two variables, psychiatric history, and counseling and psychiatric treatment for Internet gaming, which were not considered important factors in the analysis because they formed the single largest category. In addition, the following six variables with *p*-values less than .5: gender, residence, current employment, academic background, economic level, and Internet gaming start date were omitted. Finally, 14 variables were selected as input variables, which included demographic and game style factors. Game style factors were derived from the Internet Addiction Survey 2013 conducted by the Korea National Information Society Agency (2013).

This study initially used 22 variables that were identified from discussions among experts. Because there were very few related studies, we did not choose variables from the existing literature. The expert group consisted of psychiatrists, psychologists, and data scientists of medical informatics. They had more than 3 years of experience in addiction research. The reliability of the initial 22 variables was determined by the experts. Finally, we matched six training data sets to four test data sets. The analysis has been illustrated in Figure 1.

Statistical analysis

The entire sample of 1,022 participants was analyzed using the decision tree analysis model in IBM SPSS modeler 16.0. We applied the CHAID algorithm in the analysis. In addition, we conducted descriptive analyses, two independent sample *t*-tests, and PSM using IBM SPSS Statistics version 21.0.

Ethics

The study procedures were carried out in accordance with the Declaration of Helsinki. The Institutional Review Board

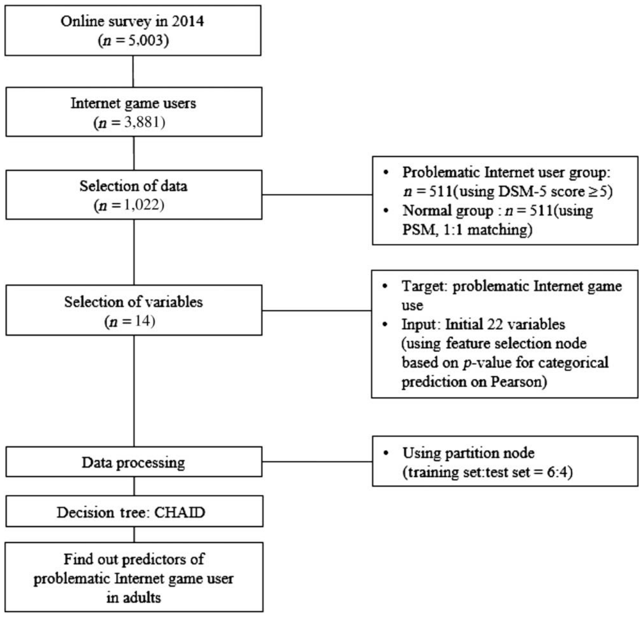

Figure 1. The research process

of Catholic University (IRB number: KC15EISI0103) approved the study. Online informed consent was obtained from all participants and information relating to the identity of the participants was removed from the data.

RESULTS

Participants' general characteristics

As shown in Table 1, 59.8% of the respondents lived in Seoul, and 59.9% were male. The respondents ranged in age from their 20s to 40s, and most were between 30 and 39 years old (45.3%). Among the respondents, 39.3% were office workers, and marital status had a similar distribution. Most (85.3%) of the respondents reported poor or fair income levels, and 97.3% reported no previous psychiatric history.

Participants' gaming characteristics

Table 2 summarizes Internet gaming characteristics. Among all participants, 77% played games at home and 97.9% played games on a PC or mobile device, such as a smartphone or tablet. Many (70.3%) of the respondents played Internet games alone, and 69.6% perceived by themselves that they were obsessed with Internet gaming. The distribution for community membership was similar across groups: 58.1% of participants had attended offline Internet gaming community meetings. Most respondents (59.8%) played only one game, and 57.1% reported that their favorite game styles were MMORPGs, real-time strategy, or sports games. There were similar distributions between groups for the time at which individuals began Internet gaming, which occurred during elementary, middle or high school, or after graduating high school. Finally, 96.5% had no prior counseling or psychiatric treatment for Internet gaming.

Table 3 summarizes Internet gaming costs and time. There was a significant difference between the normal

Table 1. Participants' general characteristics

Characteristics	Frequency	%
Residence		
Seoul	611	59.8
Metropolitan area	411	40.2
Gender		
Male	612	59.9
Female	410	40.1
Age (years)		
20–29	357	34.9
30–39	463	45.3
40–49	202	19.8
Academic background		
High school graduate or less	75	7.3
College graduate	811	79.4
Graduate school	136	13.3
Employment		
Office worker	402	39.3
Administrative position	78	7.6
Service industry	74	7.2
Professional tech worker	130	12.7
Production employee	26	2.5
Student	145	14.2
Housewife	85	8.3
Unemployed and other	82	8
Marital status		
Single	518	50.7
Couple	504	49.3
Income level		
Poor	449	43.9
Fair	423	41.4
Good	150	14.7
Psychiatric history		
No	994	97.3
Yes	28	2.7
Condition		
Normal comparison group	511	50
Problematic Internet game user group	511	50
Total	1,022	100

Note. Single: never married, divorced, separated, or widowed; Couple: married or living with a partner.

comparison and the problematic Internet game user groups for the average time spent gaming on weekdays ($t = -6.382$, $p < .001$), the average time spent gaming on weekends and holidays ($t = -6.516$, $p < .001$), maximum gaming time ($t = -5.884$, $p < .001$), and gaming costs ($t = -7.150$, $p < .001$). The problematic Internet game user group spent an average of 2.92 hr on weekdays and 4.19 hr on weekends and holidays gaming. On average, the problematic Internet game user group spent 1.5 times more hours gaming than the comparison group did, and the average maximum game time for the problematic Internet game user group was 1.6 times more hours than in the comparison group. In addition, the problematic Internet game user group spent 2.8 times more money on Internet gaming than the comparison group did.

Decision tree: Rule induction method (CHAID)

In this CHAID algorithm, we extracted six rules related to problematic Internet game use. The total prediction rate was 70.41%, as presented in Table 4. This is a reasonable level of accuracy; thus, the results of this study were accepted. In the decision tree analysis, the value of the parent and child nodes determined the tree depth. The tree depth could vary depending on the value of either the parent or child node. Thus, before the analysis, we set the parent node value to 50 samples and the child node value to 25 samples. The CHAID algorithm identified predictive factors using the relative importance between variables. Six variables and their importance rates were key predictors: gaming costs (50%), average weekday gaming time (23%), offline Internet gaming community meeting attendance (13%), average weekend and holiday gaming time (7%), marital status (4%), and self-perceptions of problematic Internet game use (3%). Accordingly, the predicted percentage was 86% with three main factors: game costs, average weekday gaming time, and offline Internet gaming community meeting attendance.

Using the CHAID algorithm, we identified six rules, which are summarized in Table 5. Figure 2 shows the results of the decision tree analysis. Rule #1 states that the average monthly cost of Internet gaming threshold was \$45.02; thus, gamers who spent, on average, more than \$45.02 per month had a higher risk of problematic Internet game use (from 51.57% to 83.33%, node 4). Rule #2 states that gamers spent an average of \$4.50–\$45.02 per month on Internet gaming and attended offline Internet gaming community meetings. When the average weekday gaming time was less than 1 hr, there was a 56.25% probability of problematic Internet game use (from 72.97% to 56.25%, node 13). Rule #3 states that gamers spent between \$4.50 and \$45.02 per month on Internet gaming and attended offline Internet gaming community meetings. When gamers spent, on average, more than 1 hr on a weekday gaming, they were considered to be at high risk for problematic Internet game use (from 64.82% to 81%, node 14). Rule #4 is node 15, which suggests that gamers spent an average of \$4.50–\$45.02 per month on gaming costs and did not attend offline Internet gaming community meetings. Gamers who were single and recognized that they were obsessed with Internet gaming had a high risk of problematic Internet game use (from 63.16% to 75%). Rule #5 is node 8, which indicates that a gamer's monthly Internet gaming costs were less than \$4.50, and the average weekday gaming time was more than 1 hr (58.06%). Finally, rule #6 is node 6, in which gamers did not spend money on gaming, and the average weekend and holiday gaming time was more than 3 hr (54.84%).

As shown in Figure 2, the risk ratio of the highest parent node was 51.57%. Several rules (2, 5, and 6) that had risk ratios less than 60% were not accepted in this study as the final patterns of problematic Internet game use. Therefore, we determined three patterns of problematic Internet game use using risk ratio: rules 1, 3, and 4. Participants who followed rule #1 as cost-consuming gamers (node 4, risk ratio = 83.33%), rule #3 as socializing gamers (node 14, risk ratio = 81%), and rule #4 as solitary gamers (node 15, risk ratio = 75%).

Table 2. Participants' gaming characteristics

	Normal comparison group ($n = 511$)		Problematic Internet game user group ($n = 511$)		Total	
	Frequency	%	Frequency	%	Frequency	%
Gaming place						
Home	399	78.1	388	75.9	787	77
School	1	0.2	4	0.8	5	0.5
PC room	50	9.8	88	17.2	138	13.5
Game room	2	0.4	1	0.2	3	0.3
Outside (subway, bus, etc.)	54	10.6	30	5.9	84	8.2
Other	5	1	0	0	5	0.5
Type of gaming device						
PC	186	36.4	271	53	457	44.7
Console	9	1.8	12	2.3	21	2.1
Mobile device (smartphone, tablet, etc.)	316	61.8	228	44.6	544	53.2
Gaming participants						
Alone	375	73.4	343	67.1	718	70.3
With family	25	4.9	21	4.1	46	4.5
With friends in an offline space	38	7.4	54	10.6	92	9
With an online gaming partner	73	14.3	93	18.2	166	16.2
Self-perception of addictive Internet game use						
Not at all	33	6.5	22	4.3	55	5.4
A little	161	31.5	95	18.6	256	25
Much	277	54.2	302	59.1	579	56.7
Very much	40	7.8	92	18	132	12.9
Community membership						
No	315	61.6	213	41.7	528	51.7
Yes	196	38.4	298	58.3	494	48.3
Offline Internet gaming community meeting attendance						
No	374	73.2	220	43.1	594	58.1
Yes	137	26.8	291	56.9	428	41.9
Internet gaming method						
Play only one game	292	57.1	319	62.4	611	59.8
Choose different games on each occasion	219	42.9	192	37.6	411	40.2
Favorite gaming genres						
FPS	42	8.2	64	12.5	106	10.4
MMORPG	88	17.2	131	25.6	219	21.4
RPG	3	0.6	4	0.8	7	0.7
RTS	100	19.6	120	23.5	220	21.5
TPS	2	0.4	4	0.8	6	0.6
Racing	37	7.2	35	6.8	72	7
Sports	71	13.9	74	14.5	145	14.2
Arcade	10	2	8	1.6	18	1.8
Action	2	0.4	3	0.6	5	0.5
Other	156	30.5	68	13.3	224	21.9
Beginning of the Internet gaming						
Elementary school	119	23.3	126	24.7	245	24
Middle or high school	142	27.8	153	29.9	295	28.9
After graduating high school	148	29	142	27.8	290	28.4
30–39 years	77	15.1	74	14.5	151	14.8
40–40 years	25	4.9	16	3.1	41	4
Counseling and psychiatric treatment for Internet gaming						
No	508	99.4	478	93.5	986	96.5
Yes	3	0.6	33	6.5	36	3.5
Total	511	50	511	50		1,022

Note. FPS: first-person shooter; MMORPG: massive multiplayer online role-playing game; RPG: role-playing game; RTS: real-time strategy; TPS: third-person shooter.

Table 3. Gaming costs and time characteristics

Characteristics	Normal comparison group ($n = 511$)		Problematic Internet game user group ($n = 511$)		*t*-Test	
	Mean	*SD*	Mean	*SD*	*t*-Value	Significance
Average weekday gaming time	1.95	2.051	2.92	2.733	–6.382	$p < .001$
Average weekend and holiday gaming time	2.77	3.369	4.19	3.551	–6.516	$p < .001$
Maximum gaming time	3.65	4.648	5.86	7.103	–5.884	$p < .001$
Gaming costs	$10.29	$29.58	$29	$51.24	–7.150	$p < .001$

Note. ***$t_{0.001} = 3.291$; time unit: hours; time and cost unit: per day; the exchange rate for Korean won to the U.S. dollar is 1,120.70 won (June 2015).

Table 4. Misclassification table (prediction rate) according to the decision tree analysis

Observation	Expected rate			Prediction rate (%)
	Normal comparison group	Problematic Internet game user group	Total	
Normal comparison group	195	98	293	66.55 (specificity)
Problematic Internet game user group	81	231	312	74.04 (sensitivity)
Total	276	329	605	70.41 (accuracy)

DISCUSSION

This study identified predictors and patterns of problematic Internet game use including game style factors.

Six variables were revealed as predictors of problematic Internet game use: gaming costs, average weekday gaming time, offline Internet gaming community meeting attendance, average weekend and holiday gaming time, marital status, and self-perceptions of problematic Internet game use.

Gaming costs and average weekday gaming time were the most important factors in predicting problematic Internet game use. According to the Ministry of Science, ICT and Future Planning (MSIP), problematic Internet gaming costs (including Internet game community dues, gaming item purchases, and game usage fees) and average weekday gaming time were $5.60 (monthly average) and 2.9 hr, respectively, in 2014 (National Information Society Agency, 2014). However, using the CHAID algorithm, results from this study showed that, in the problematic Internet game user group, the average threshold of monthly cost of Internet gaming was $4.50 or $45.02, and the time spent was 2.92 hr. The difference in costs between the MSIP records and this study may be due to the characteristics of the participants and distinctions in research tools. This study focused on adults over the age of 20 years and used the DSM-5 criteria to define problematic Internet game use, while the MSIP records covered all ages (3–59 years), including children and adolescents, and used the Korean Internet addiction scale.

Studies as well as governmental records on game style factors were only descriptive (Allison et al., 2006; Festl, Scharkow, & Quandt, 2013; Kuhn & Gallinat, 2014; Lemmens et al., 2011; National Information Society Agency, 2014) and could not explain the relationships with the risk of problematic Internet game use. However, it was found that game style factors may act as predictors of problematic Internet game use. In addition, offline Internet gaming community meeting attendance was first identified as an important factor in problematic Internet game use. The game style factors are simple and quick to figure out using uncomplicated questions or observation of family and friends around game users. Therefore, the results from this study provide direction for future work on pre-screening groups at a high risk of problematic Internet game use in the population.

In addition, we identified the patterns of problematic Internet game use and found that problematic Internet game use was classified into three types based on six rules: cost-consuming, socializing, and solitary gamers. For the cost-consuming gamers, the average monthly cost of Internet gaming threshold was $45.02. The cost-consuming gamer spent a large amount of money on Internet gaming. The socializing gamer spent both money and time on gaming and attended offline Internet gaming community meetings. The solitary gamer spent less than $45.02 on gaming and did not attend offline Internet gaming community meetings. They were single, which was defined as never having been married, divorced, separated, or widowed, and recognized that they were obsessed with Internet gaming. Prior studies suggested that addictive Internet game use is associated with a shortage of social or romantic contact (Allison et al., 2006; Porter, Starcevic, Berle, & Fenech, 2010). As problematic Internet game use is believed to be a heterogeneous feature (Young, 1999), it sounds reasonable that specific subgroups exist. Some studies have suggested that, while on one hand, internalizing problems such as depression or anxiety were related to the problematic Internet game use; on the other hand, externalizing problems such as sensation seeking, novelty seeking, or impulsivity were also related based on comorbidity and personality factors (De Leo & Wulfert, 2013). Although these results are hard to compare with our

Table 5. The five subtypes of problematic Internet game users

Rule #	Pattern				Subtype
1	Gaming costs > \$45.02 ($n = 40$, 83.33%, node 4)				Cost-consuming gamer
2	\$4.50 < Gaming costs ≤ \$45.02 ($n = 164$, 64.83%)	Offline Internet gaming community meeting attendance = Yes ($n = 108$, 72.97%)	Average weekday gaming time ≤ 1 hr ($n = 27$, 56.25%, node 13)		–
3	\$4.50 < Gaming costs ≤ \$45.02 ($n = 164$, 64.83%)	Offline Internet gaming community meeting attendance = Yes ($n = 108$, 72.97%)	Average weekday gaming time > 1 hr ($n = 81$, 81%, node 14)		Socializing gamer
4	\$4.50 < Gaming costs ≤ \$45.02 ($n = 164$, 64.83%)	Offline Internet gaming community meeting attendance = No ($n = 56$, 53.33%)	Self-perceptions of addictive Internet game use = Yes ($n = 48$, 63.16%)	Marital status = Single ($n = 30$, 75%, node 15)	Solitary gamer
5	Gaming costs ≤ \$4.50 ($n = 55$, 44%)	Average weekday gaming time > 1 hr ($n = 36$, 58.06%, node 8)			–
6	Gaming costs = 0 ($n = 53$, 29.61%)	Average weekend and holiday gaming time > 3 hr ($n = 17$, 54.84%, node 6)			–

Note. The exchange rate for Korean won to the U.S. dollar is 1,120.70 won (June 2015).

patterns, internalizing problems may be associated with the solitary type and externalizing problems may be associated with the cost-consuming or socializing type. However, further research is needed to identify the subgroups covering various factors, such as demographic, psychological, personality, comorbidity, and gaming style factors. Even though we classified the types based on only some factors, including demographic and gaming characteristics, identifying the specific subgroups can help us to understand the problematic Internet game use and provide guidance toward the customized screening of Internet game users.

In this study, the game style factors such as gaming costs, gaming time, and attendance of offline Internet gaming community meetings were found to be important predictors and factors making up the patterns in problematic Internet game use. Awareness and identification of risk factors and patterns make it possible to develop screening strategies. Therefore, game style factors might be considered during the development of methods for screening problematic Internet game use. Indeed, further research is needed on these areas.

There were several limitations in this study. First, we defined the problematic Internet game user group as participants who self-rated at least five of nine items of IGD criteria. However, the DSM-5 criteria did not account for online surveys, and IGD lacks an established definition. Such issues regarding the reliability and validity of the DSM-5 criteria for IGD remain contentious (Petry et al., 2014). Thus, future research should develop the proper criteria, which can be implemented in future studies for problematic Internet game use. Second, our findings were based on online surveys, as it was not possible to collect actual gaming time and costs. There were differences between the responses and actual values for gaming time and costs. Thus, our cutoff values for gaming time and costs have limited applicability in service settings. Future research should collect actual gaming costs and time to identify cutoffs for problematic Internet game use. Third, the game style factors in this study were derived from the Internet Addiction Survey 2013 conducted by the National Information Society Agency (2013) and experts' discussion. Thus, future research should be conducted with additional variables. Fourth, we did not use game genre as final input data although it was included in the survey, because this variable was excluded from the analysis by feature selection. However, some findings indicated that problematic Internet game use is associated with an individual's preferred game genres (Kuss & Griffiths, 2011). Adolescent users of role-playing games, including MMORPGs, showed significantly higher Internet addiction scores than did web board and sports game players (Lee et al., 2007). Thus, future research should examine the relationship between problematic Internet game use and gaming genres.

Fifth, we collected information on gaming time and cost based on self-report. Indeed, there may be differences between perceived gaming time and actual gaming time because expert players are predisposed to warping their gaming time and one's perception of time is often influenced by circumstances, such as excitement, drugs, aging, and body temperature (Rau, Peng, & Yang, 2006). To develop predictive algorithms for problematic Internet game use,

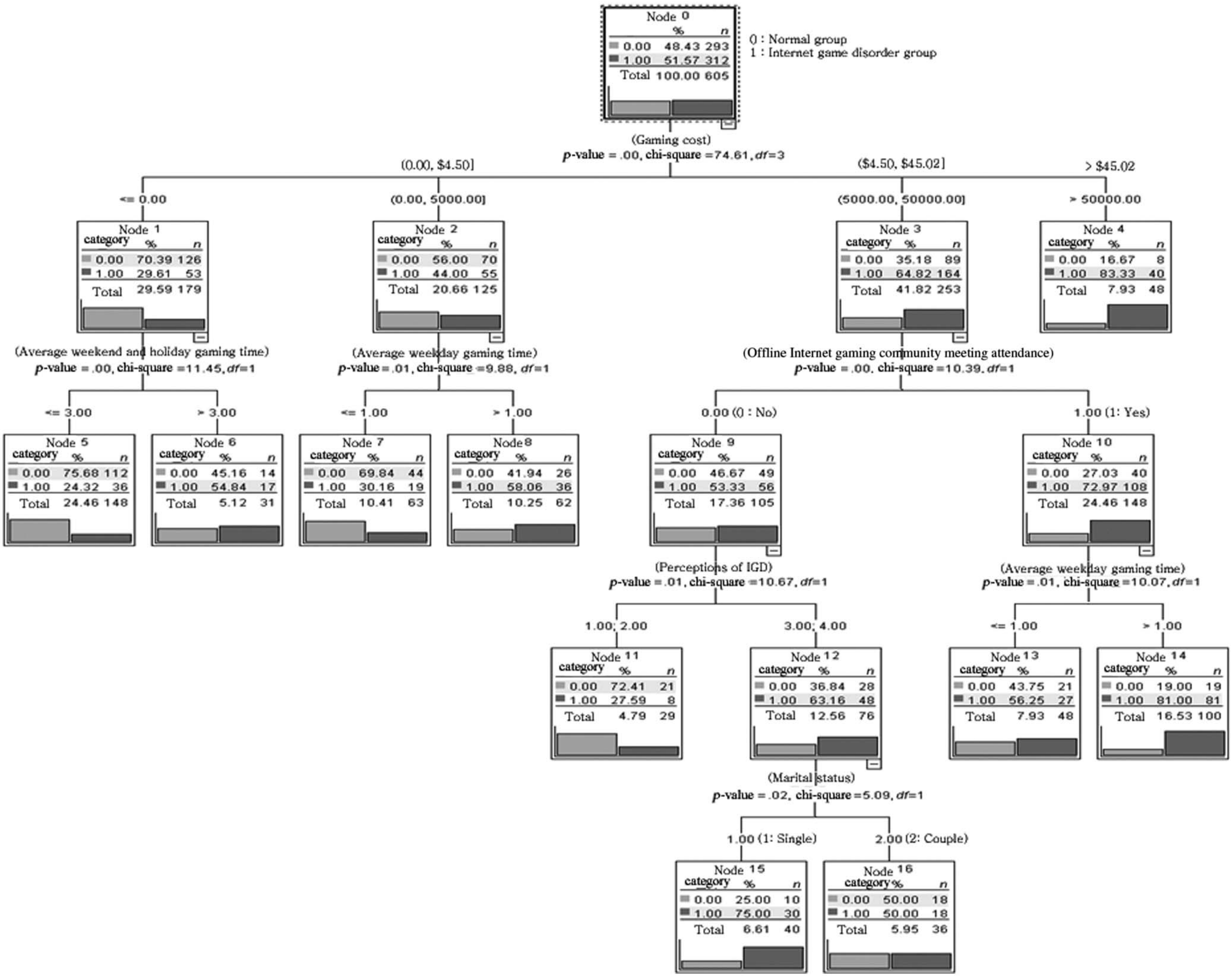

Figure 2. The decision tree

developers need to use the real gaming time and cost depending on service targets and detailed circumstances. Finally, this study was exploratory, and we proposed three patterns of problematic Internet game use. Future studies should determine the clinical value of these types of problematic Internet game use. Moreover, additional research is needed to examine the types of problematic Internet game use and to develop tailored screening, treatment, or prevention programs.

Despite these limitations, this study yielded several valuable implications. First, we identified predictors of problematic Internet game use, including gaming costs, the average weekday and weekend and holiday gaming times, and offline Internet gaming community meeting attendance. This study has included game style factors as predictors while many previous studies on risk factors focused on psychological or personality factors. Furthermore, we compared the game style factors to each other and decided which factors were important. To identify various types of risk factors that increase vulnerability to problematic Internet game use, it is important to establish screening strategies.

Second, this study proposed several patterns of problematic Internet game use, which were useful in classifying problematic Internet game users into subtypes. Identifying the subgroups can promote the understanding of problematic Internet game use and may provide guidance for developing customized screening for Internet game users.

Third, we have studied the problematic Internet game use in adults while many studies of Internet game addicts focused on children and adolescents (Kuss & Griffiths, 2012; Van Rooij, Schoenmakers, Vermulst, Van den Eijnden, & Van de Mheen, 2011). However, Internet gaming is not restricted to children and adolescents. In the United States, the average age of Internet gamers is 30 years (Kuhn & Gallinat, 2014). Therefore, this study may provide direction for future work on the screening of problematic Internet game use in adults.

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