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Psychometric Properties of the Problematic Online Gaming Questionnaire Short-Form and Prevalence of Problematic Online Gaming in a National Sample of Adolescents

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Abstract

The rise and growing popularity of online games has led to the appearance of excessive gaming that in some cases can lead to physical and psychological problems. Several measures have been developed to explore the nature and the scale of the phenomenon. However, few measures have been validated psychometrically. The aim of the present study was to test the psychometric properties of the 12-item Problematic Online Gaming Questionnaire Short-Form (POGQ-SF) and to assess the prevalence of problematic online gaming. Data collection was carried out to assess the prevalence of problematic online gaming in a national representative adolescent sample by using an offline (pen and pencil) method. A total of 5,045 secondary school students were assessed (51% male, mean age 16.4 years, $SD=0.9$ years) of which 2,804 were gamers (65.4% male, mean age 16.4 years, $SD=0.9$ years). Confirmatory factor analysis was applied to test the measurement model of problematic online gaming, and latent profile analysis was used to identify the proportion of gamers whose online game use can be considered problematic. Results showed that the original six-factor model yielded appropriate fit to the data, and thus the POGQ-SF has appropriate psychometric properties. Latent profile analysis revealed that 4.6% of the adolescents belong to a high risk group and an additional 13.3% to a low risk group. Due to its satisfactory psychometric characteristics, the 12-item POGQ-SF appears to be an adequate tool for the assessment of problematic online gaming.

Introduction

THE GROWTH OF ONLINE VIDEOGAMING[1] has led to a minority of players developing addiction-like symptoms (e.g., overuse, withdrawal, tolerance,) and negative consequences on work, education, and/or their social relationships.[2,3] Problematic use is also associated with poor self-esteem[4,5] and depressive symptoms.[6,7] There is a lack of agreement as to the precise name and definition of the phenomenon, but the general consensus is that excessive online gaming can lead to a variety of physical/psychological problems.[8] Few studies have examined the prevalence of problematic gaming. Gentile[9] reported that 8.5% of American children aged 8–18 years exhibited pathological playing patterns. Rehbein et al.[10] found that 3% male and 0.3% female ninth graders were dependent on videogames, with 5% boys and 0.5% girls at risk for developing dependence. Van Rooij et al.[11] reported that 1.5% of Dutch children aged 13–16 years were addicted online gamers.

In order to obtain reliable prevalence data, it is important to use psychometrically validated measurement tools.[12] Unfortunately, there is lack of such tools, and most have been modified from other questionnaires without reliability/validity testing. This includes those based on Internet addiction (e.g., Internet Addiction Test[13]), pathological gambling (using DSM-IV criteria), or behavioral addictions.[14,15] An additional problem is that many tools focus exclusively on Massively Multiplayer Online Role Playing Games (MMORPGs).[16,17] In

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order to include all online gamers, an empirically based questionnaire comprising 18 items—the Problematic Online Gaming Questionnaire (POGQ)—was developed by the authors.[8]

Koronczai et al.[18] claimed that suitable measures should meet six requirements: (a) comprehensiveness (i.e., examining more, possibly all, aspects of problematic online gaming); (b) brevity (to assess the more impulsive population, as well and to facilitate incorporation into time limited surveys); (c) reliability/validity for different methods of data collection (online, paper and pencil self-rating, face to face); (d) reliability/validity for different age groups (adolescents and adults); (e) cross-cultural reliability/validity; and (f) validated on clinical samples. The measures should also serve as a basis for defining dependence cutoff scores.

The POGQ fits the first two requirements. Moreover, it is a psychometrically robust measure among large convenience samples of adult online gamers (for details of POGQ development, see our earlier study[8]). However, there is great need for measures suitable for survey type research in an offline data collection setting that are reliable/valid for adolescents.[19] Therefore, the POGQ was reduced to a 12-item version, and applied to an offline adolescent sample using pen and pencil data collection (fulfilling the third and fourth criteria above).

The aim of the present study was twofold: (a) to test the psychometric properties of the POGQ-SF, including gender invariance, on a nationally representative adolescent sample, as until recently it had only been used on adult gamer samples; (b) to assess the prevalence of problematic online gaming in a nationwide adolescent sample, as only two nationally representative adolescent studies in the United States[9] and Germany[10] have been published. Therefore, this study makes a significant contribution to the literature.

Methods

Participants and procedure

In order to obtain a nationwide adolescent sample, data were collected using the European School Survey Project on Alcohol and Other Drugs (ESPAD).[20] This international collaboration collects compulsory data on smoking, alcohol, and drug use. However, each country has the opportunity to include optional questions. In 2011, Hungary included a short section to assess online gaming.

The target population of the ESPAD project is adolescents aged 16 years. To obtain a representative group sample, three different grades (8–10) were included in the Hungarian sample, each containing a proportion of the target population.[21] The survey applied an internationally homogenous stratified random sampling method based on region (central/western/eastern Hungary), grade (8–10), and class type (primary general, secondary general, secondary vocational, and vocational classes). The sampling unit was the class, and every classroom student present completed the questionnaire. Refusal rate was 15%, and therefore data were weighted due to skewed nonresponse. To adjust for the variations among different sample groups (to match the composition of the respondents with the sampling frame), data were weighted by strata with the matrix weighting method according to the National Education Information System (KIR-STAT).[21]

Students were surveyed in March 2011.[21] Questions regarding online gaming were only included for the representative sample of 9th–10th graders in secondary general and secondary vocational schools ($n = 5,045$). The present analysis was carried out on the subsample of those who had played online games in the past month ($n = 2,804$; 55.6% of total sample). After removing cases where POGQ questions were missing, the final sample size was 2,774.

Measures

Major sociodemographic information (age, grade, gender, residence) and online gaming habits (e.g., type of online games played, frequency of playing, duration of typical gaming sessions) were collected. Additionally, psychological characteristics, including self-esteem (Rosenberg's Self-Esteem Scale [RSES][22]) and depressive mood (short-form [6-item] Center of Epidemiological Studies Depression-Scale [CES-D][23]) were assessed. RSES is a 10-item self-report unidimensional measure of global self-esteem assessing feelings of self-worth and self-acceptance. Items were answered on a 4-point scale ("strongly agree" to "strongly disagree"). Scores ranged from 10–40, with higher scores indicating higher self-esteem.[24] Cronbach's alpha was 0.857. CES-D is a unidimensional scale, not designed to diagnose clinical depression but to assess depressive symptom levels. Items were answered on a 4-point scale ("rarely or never" to "most of the time"). Scores ranged from 4–24, with higher scores indicating higher depressive mood level.[24] Cronbach's alpha was 0.807.

Problematic online gaming was assessed using the 12-item POGQ-SF (see Appendix). The POGQ was originally an 18-item scale with good psychometric properties based on wide empirical content developed by the authors.[8] It measures six dimensions of problematic use (preoccupation, overuse, immersion, social isolation, interpersonal conflicts, and withdrawal). The 12-item version of POGQ was developed by selecting two items from each factor. Item selection took into account preservation of high content validity and selection of the highest possible factor loadings. The reason for a short-form POGQ was to develop a measure that can be used in survey type research, brief enough to assess more impulsive populations, and which facilitates incorporation into time limited surveys.

Statistical analysis

To test the model, confirmatory factor analysis (CFA) was used with maximum likelihood estimation with robust standard errors (MLR) in MPLUS 6.0. To evaluate goodness of fit, a p value of chi square smaller than 0.05 for test of close fit was used. Further fit indices included comparative fit index (CFI), Tucker–Lewis Fit index (TLI), root mean square error of approximation (RMSEA) and its 90% confidence interval (90% CI), and standardized root mean square residual (SRMR). For both CFI and TLI, values greater than 0.95 indicate a good fit, while values of RMSEA and SRMR should be less than 0.05 and 0.10 respectively for a well-fitting model.[25] In order to compare alternative nested models estimated with maximum likelihood estimation with robust standard errors, Satorra–Bentler scaled $\Delta\chi^2$ test (S-B $\Delta\chi^2$-test)[26] was applied to determine the better fitting model.

Testing structural and measurement invariance between gender, a series of multigroup CFAs[27] was carried out. First, the measurement model was estimated freely in boys and girls. Second, four nested models with increasing constraints were estimated, including one model in which factor loadings and intercepts were freely estimated (configural invariance), one model in which factor loadings were set equal (metric invariance), one model in which factor loadings and intercepts were set as equal in both groups (scalar invariance), and one model in which residual variances were set equal (uniqueness invariance). The traditional chi square difference test (S-B $\Delta\chi^2$-test) is usually used to compare two nested models, but this method is sensitive to the model's complexity and large sample size.[28,29] Therefore the recommendations of Cheung and Rensvold[29] and Chen[28] for comparing two nested models were followed: cut-off values of ΔCFI <0.01 and ΔRMSEA <0.015 were used for testing metric, scalar, and uniqueness invariance. The models were considered invariant in condition when both ΔCFI and ΔRMSEA indices were below the cut-off values.

In order to identify the gamers whose online game use was considered as problematic, latent profile analysis (LPA) was selected (carried out in MPLUS 6.0). The indicator variables were the sum score of each dimension of POGQ, as observed variables. LPA is a mixture modeling technique used to identify groups of people (categorical latent variable) that are similar in their responses to certain variables, in this case scores given for the six POGQ dimensions (continuous manifest variables).[30] The analysis was performed with two to four classes on the weighted adolescent subsample playing online games during the last month (n = 2,774). To determine the number of latent classes, several indices were used. Measures of parsimony of each model (e.g., Akaike Information Criteria [AIC], Bayesian Information Criteria [BIC], and Sample size adjusted Bayesian Information Criteria [SSABIC]) were used, lower values indicating more parsimonious models. The Entropy criterion was also examined, determining the accuracy of classifying people into their respective profiles, with higher values indicating better fit. Finally, the Lo-Mendell-Rubin Adjusted Likelihood Ratio Test (LMRT) was used. This statistically compares the fit of the target model (e.g., three-class model) to a model with one class less (e.g., two-class model). A p value of less than 0.05 indicates the tested model fits better than the previous one.[31] For CFA, the unweighted sample of the 2,774 cases was used. All other analysis was conducted on the weighted sample (described above). Missing data were treated with FIML method. Covariance coverage was greater than 0.98 in CFA.

To test the validity of the POGQ further, the LPA classes along a few variables (i.e., gender, time spent gaming, grade point average, self-esteem, level of depressive symptoms) relevant to the phenomenon of problematic online gaming were compared. For these comparisons, Wald's chi square test of mean equality for latent class predictors in mixture modeling was used (for description of analysis, see www.statmodel.com/download/meantest2.pdf).

Results

Descriptive statistics

The total sample (n = 5,045, 51% male, mean age 16.4 years, SD = 0.87 years) was divided into two groups. Those who played online games in the month preceding data collection were classed as "gamers" (G), and those who had not played were classed as "nongamers" (NG). More than half (55.6%) of the sample's participants were gamers (n = 2804). Two-thirds of gamers (65.4%) were male compared to 32.9% of nongamers (χ^2 = 403.29, p < 0.001). The mean age of gamers and nongamers was 16.4 years (SD_G = 0.85; SD_{NG} = 0.89 years; F = 0.009, p = 0.926).

Confirmatory factor analysis

A six-factor solution on the 'gamer' group (n = 2774) with CFA was tested. The model provided an optimal fit to the data (χ^2 = 277.35, df = 39, p < 0.001; CFI = 0.972; TLI = 0.953; RMSEA = 0.047 [0.042–0.052] Cfit > 0.90; SRMR = 0.025) (Table 1). Alternatively, the degree of fit of a one-factor model (χ^2 = 1549.20, df = 54, p < 0.001; CFI = 0.82; TLI = 0.79; RMSEA = 0.100 [0.096–0.104] Cfit < 0.001; SRMR = 0.064) and a model with one second ordered factor (χ^2 = 528.30; df = 48, p < 0.001; CFI = 0.94; TLI = 0.92; RMSEA = 0.060 [0.056–0.065]; Cfit < 0.001; SRMR = 0.042) were estimated. The original six-factor model yielded superior fit compared to the one-factor model (S-B $\Delta\chi^2$-test = 1137.3; Δdf = 15, p < 0.0001) and the second ordered factor model (S-B $\Delta\chi^2$-test = 246.2; Δdf = 9, p < 0.0001). In the six-factor model, the factor loadings were higher than 0.70 with their respective factor. The correlations between factors ranged between 0.82 and 0.57 (Table 1). The highest correlation was between social isolation and interpersonal conflict, and the lowest correlation was between social isolation and preoccupation. Based on the CFA analysis, the composite reliability and average variance extracted indices[32,33] were calculated. The composite reliability of each dimension was greater than 0.60 (Table 1). The average variance extracted from each scale was adequate and greater than 0.50 (Table 1). The discriminant validity coefficients with the square root of the average variance extracted were also calculated. Although discriminant validity indices were high, the correlations between factors were strong. Therefore the relatively weak discriminant validity of each dimension represented that these dimensions are closely related component of the construct of problematic online gaming.

Gender invariance of the six-factor model, including configural, metric, and scalar invariances, was tested. The fit indices are reported in Table 2. The first test of configural invariance measured whether POGQ-SF was best described by a six-factor structure for boys and girls. The results showed that the configural invariance model fitted the data reasonably well (RMSEA = 0.053 Cfit >0.135, CFI = 0.952). In order to confirm metric invariance, factor loadings were constrained to be equal across genders; intercepts and residual variances were freely estimated; and factor means were fixed to 0 in boys and girls. The constrained model yielded acceptable model fit (RMSEA = 0.055 Cfit >0.050, CFI = 0.946). The changes in chi square between the configural and metric invariant model were significant (S-B $\Delta\chi^2$-test = 40.3; df = 6, p < 0.001). However, ΔCFI = 0.006 and ΔRMSEA = 0.002 were smaller than the cut-off values. These results confirm that factor loadings were invariant across genders. To establish scalar invariance, intercepts and factor loadings were constrained to be equal across the two groups; the residual variances were freely estimated; and factor means were set to 0 in one group and free in the other. The changes in chi square between the metric and scalar invariant model were significant (S-B $\Delta\chi^2$-test = 24.5; df = 6, p < 0.001). However, ΔCFI = 0.003 and ΔRMSEA = 0.001 were less than the cut-off values,

Table 1. Confirmatory Factor Analyses of the 12-Item POGQ-SF on the National Sample of Hungarian Adolescents

	Preoccupation	*Immersion*	*Withdrawal*	*Overuse*	*Interpersonal conflict*	*Social isolation*
When you are not gaming, how often do you think about playing a game or think about how would it feel to play at that moment?	0.83					
How often do you daydream about gaming?	0.86					
How often do you lose track of time when gaming?		0.80				
How often do you play longer than originally planned?		0.71				
How often do you get restless or irritable if you are unable to play games for a few days?			0.81			
How often do you feel depressed or irritable when not gaming only for these feelings to disappear when you start playing?			0.83			
How often do you feel that you should reduce the amount of time you spend gaming?				0.83		
How often do you unsuccessfully try to reduce the time you spend on gaming?				0.85		
How often do you argue with your parents and/or your partner because of gaming?					0.76	
How often do the people around you complain that you are gaming too much?					0.77	
How often do you fail to meet up with a friend because you were gaming?						0.78
How often do you neglect other activities because you would rather game?						0.83
Cronbach's alpha	0.83	0.72	0.80	0.83	0.73	0.78
Average variance extracted*	0.57	0.71	0.67	0.71	0.59	0.65
Composite reliability**	0.73	0.83	0.80	0.82	0.74	0.79
			Correlations between factors			
Preoccupation	(0.75)$					
Immersion	0.77	(0.84)				
Withdrawal	0.70	0.77	(0.82)			
Overuse	0.71	0.54	0.66	(0.84)		
Interpersonal conflict	0.74	0.71	0.81	0.82	(0.77)	
Social isolation	0.57	0.67	0.81	0.63	0.82	(0.81)
Mean	3.41	4.48	2.89	3.18	3.12	2.66
SD	1.77	2.16	1.58	1.75	1.64	1.81

Note: Empty cells represent the factor loadings that are fixed to 0; all other factor loadings are significant at least at $p < 0.001$. Cronbach's alpha of the total Problematic Online Gaming Questionnaire is 0.91. *Calculated by hand with the formula provided by Fornell and Larcker[33]; **Calculated by hand with the formula provided by Bagozzi and Yi.[32] $Discriminant validity coefficient based on the square root of average variance extracted.

Table 2. Goodness-of-Fit Indices for Models Testing Gender Invariance

	χ^2_{boys}	χ^2_{girls}	*df*	*CFI*	*TLI*	*RMSEA*	*Cfit of RMSEA*	*SRMR*
Single group analyses separately in boys and girls								
1. Boys only	233.5		39	0.968	0.946	0.053	0.241	0.026
2. Girls only		113.8	39	0.959	0.931	0.044	0.829	0.037
Multigroup analyses								
3. *Configural invariance:* Factor loadings and intercepts are freely estimated, and factor means are fixed to 0	210.9	204.3	84	0.952	0.924	0.053	0.138	0.127
4. *Metric invariance:* Factor loadings are fixed to be equal, intercepts are freely estimated, and factor means are fixed to 0	216.2	244.8	90	0.946	0.921	0.055	0.063	0.175
5. *Scalar invariance:* Intercepts and factor loadings are constrained	232.0	256.1	96	0.943	0.922	0.054	0.068	0.175
6. *Uniqueness invariance:* Intercepts, factor loadings, and residual variances are constrained	290.7	568.8	108	0.891	0.867	0.071	<0.0001	0.256

which indicates that scalar invariance can be established across the two groups. To test uniqueness invariance intercepts, factor loadings and uniqueness (residual variances) are constrained to be equal across genders. The changes in chi square between the scalar and uniqueness invariant model were significant (S-B $\Delta\chi^2$-test = 236.2; df = 12, $p < 0.001$). However, ΔCFI = 0.052 and ΔRMSEA = 0.017 were higher than the cut-off values, which indicates that uniqueness invariance cannot be established across the two groups. However, the uniqueness invariance is not a requirement for the comparison of each group's means.

Latent profile analysis

A latent profile analysis on the six dimensions of problematic online gaming was performed. According to the criteria listed above, the three-class solution was selected (Table 3). The AIC, BIC, and SSABIC decreased continuously as more classes were added to the analysis. However, the scale of decrease diminished after the third latent class was added. Regarding the entropy, the two-class solution provided the greatest value, but the three-class solution was also adequate. The nonsignificant *p* value of the L-M-R test clearly showed that the four-class solution should be rejected in favor of the previous one. Therefore the three-class solution was accepted.

The features of the three classes are shown in Figure 1. The first class (68% of gamers; 37.8% of total sample) represents those gamers who scored below the average on the POGQ-SF factors. The second class of gamers (23.9% and 13.3% respectively) represents the low risk for problematic use, while the third class (8.2% and 4.6% respectively) represents the high risk for problematic online gaming population. In all three groups, especially the second, the "immersion" factor showed an elevated level compared to the other five dimensions.

Gamers belonging to the high risk class were more likely to (a) be male, (b) play for more than 5 hours a day, (c) have a lower grade point average, (d) have lower self-esteem, and (e) have higher level of depressive symptoms than gamers belonging to the other two classes (Table 4).

Determination of the optimal cut-off score in order to classify online gamers as problematic gamers: sensitivity and specificity analyses

Considering the membership in the third class (high risk for problematic online gaming) as the "gold standard," the sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and accuracy of the POGQ-SF at all possible cut-off points were calculated (Table 5). Based on this analysis, a cut-off score of 32 points is an optimal cut-off to classify online gamers as problematic gamers. At this value, sensitivity is 96%, while specificity is 97% (i.e., only 4% of true problematic gamers are not identified by the measure, while only 3% of nonproblematic cases are considered problematic). In this case, PPV is 75% and NPV is 100%. This means 25% of the individuals with a positive test result are identified mistakenly, while all individuals with negative test results are identified correctly. The accuracy was 97%. Increasing the cut-off score would lead to more false negative cases, while decreasing would further increase the number of gamers mistakenly diagnosed.

Discussion

Results showed that the 12-item POGQ-SF has appropriate psychometric properties according to the CFA performed on a nationally representative adolescent sample. The results

Table 3. Fit Indices for the Latent Profile Analysis of the POGQ-SF

Number of latent classes	*AIC*	*BIC*	*SSABIC*	*Entropy*	*L-M-R test*	p
2 classes	56,966	57,079	57,019	0.944	6,650	<0.001
3 classes	54,800	54,954	54,872	0.913	2,141	<0.001
4 classes	53,905	54,100	53,995	0.912	797	0.3423

Note: AIC, Akaike Information Criteria; BIC, Bayesian Information Criteria; SSABIC, sample size adjusted Bayesian Information Criteria. L-M-R test, Lo-Mendell-Rubin adjusted likelihood ratio test value; *p*, *p* value associated with L-M-R test.

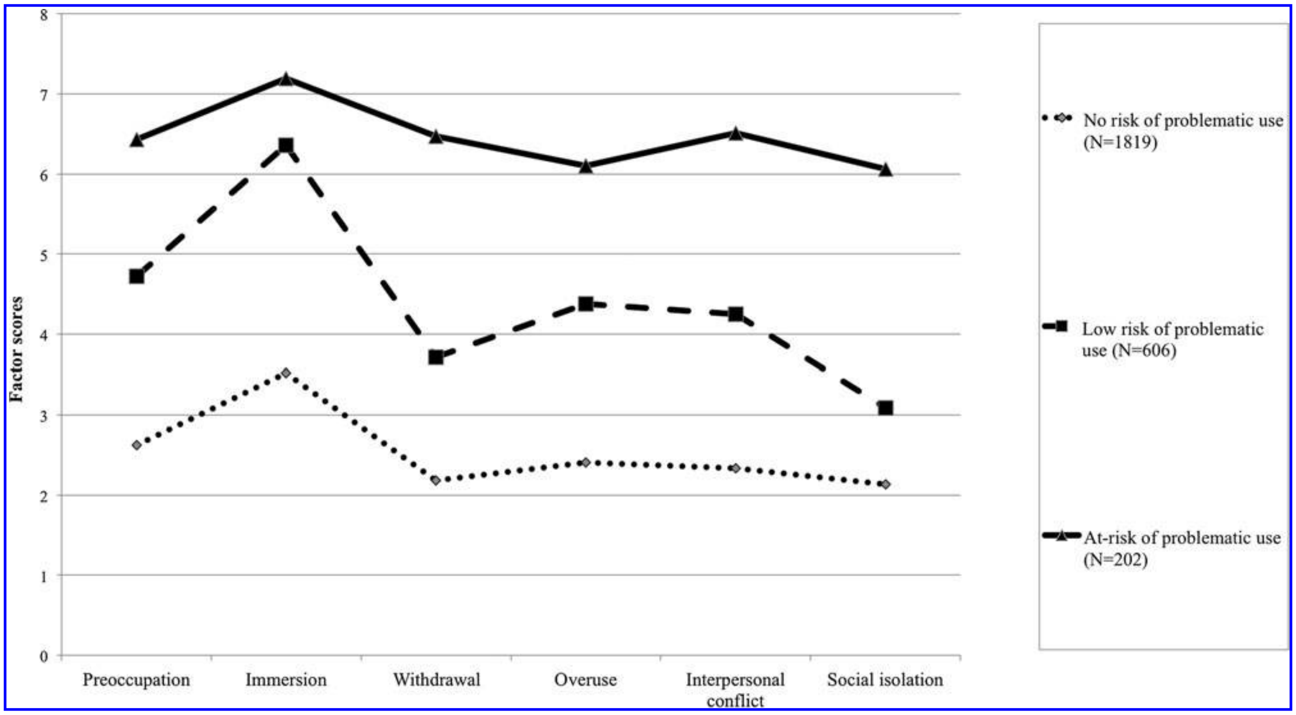

FIG. 1. Latent profile analysis on the six factors of the Problematic Online Gaming Questionnaire Short-Form (POGQ-SF).

support the gender invariance of POGQ-SF including configural, metric, and scalar invariance. However, residual invariance cannot be confirmed. Latent profile analysis revealed 8.2% of gamers (4.6% of total sample) belong to the high risk group. This prevalence value is in accordance with other large sample surveys conducted.[9,10] Results showed an additional 13.3% of adolescents (23.9% of gamers) displaying symptoms of problematic online gaming above the average. Both groups (high risk and low risk) should be analyzed thoroughly in future studies to explore those background factors that may carry risk regarding problematic online gaming.

In this study, the "immersion" dimension showed an elevated level at all three LPA classes, especially the low risk group. The two items of this dimension ("How often do you play longer than originally planned?" and "How often do you lose track of time when gaming?") indicate excessive use of online games, immersion in gaming, and losing track of time. Since low risk groups could be the focus of future prevention programs, immersion should be highlighted when developing such programs.

Gamers belonging to the high risk class were more likely to be male, play for more than 5 hours a day, have a lower grade point average, have lower self-esteem, and have a higher depression score than gamers belonging to the other two classes. These results concur with findings of other studies confirming the measurement tool's validity. Several studies claim males are at a higher risk of becoming problematic online gamers[10,34] and that problematic online gamers spend more time playing than normal gamers.[9,35,36] Some studies also note that problematic gamers' school performance is negatively affected by their gameplay[3,37] and are characterized by lower self-esteem.[4,5] Furthermore, some studies have demonstrated that depression is a comorbid disorder in problematic online gaming.[6,7]

The present study was carried out among Hungarian adolescents. Thus, to test it on cross-cultural samples in the future could be an important aim. It is also a future goal to

Table 4. Comparison of the Three Latent Classes: Testing Equality for Latent Class Predictors

	No risk class (n = *1,883*)	*Low risk class* (n = *652*)	*At risk class* (n = *221*)	*Overall test*	
				Wald χ^2	p *value*
Gender (male %)	56.2_a	83.8_b	87.2_b	235.5	< 0.001
Age (years), mean (SE)	$16.43\ (0.021)_a$	$16.31\ (0.032)_b$	$16.50\ (0.059)_a$	14.2	0.001
Game time on an average day (≥5 hours %)	8.3_a	23.5_b	44.9_c	133.6	< 0.001
Grade point average (min 10, max 50, mean 35.5; failed <20), Mean (SE)	$35.\ 83\ (0.186)_a$	$35.30\ (0.325)_a$	$33.32\ (0.524)_b$	17.7	< 0.001
Self-esteem (min 10, max 40, mean 28.5); Mean (SE)	$28.86\ (0.126)_a$	$28.17\ (0.215)_b$	$26.41\ (0.393)_c$	33.9	< 0.001
Level of depressive symptoms (min 6, max 24, mean 11.35); Mean (SE)	$11.06\ (0.076)_a$	$11.64\ (0.132)_b$	$13.00\ (0.255)_c$	54.5	< 0.001

Note: Different subscript letters (a, b, c) in the same row reflect significant ($p < 0.05$) difference between the means while same subscript letters in one row reflect non-significant difference between the means according to pair wised Wald χ^2 test of mean equality for latent class predictors in mixture modeling (www.statmodel.com/download/meantest2.pdf).

Table 5. Calculation of Cut-Off Thresholds for POGQ-SF

	True positive	*True negative*	*False positive*	*False negative*	*Sensitivity (%)*	*Specificity (%)*	*PPV (%)*	*NPV (%)*	*Accuracy (%)*
26/27	202	2,156	269	0	100	89	43	100	90
27/28	202	2,208	217	0	100	91	48	100	92
28/29	202	2,255	170	0	100	93	54	100	94
29/30	201	2,298	127	1	100	95	61	100	95
30/31	198	2,326	99	4	98	96	67	100	96
31/32	**194**	**2,361**	**64**	**8**	**96**	**97**	**75**	**100**	**97**
32/33	187	2,384	41	15	93	98	82	99	98
33/34	177	2,402	23	25	88	99	89	99	98
34/35	156	2,410	15	46	77	99	91	98	98
35/36	139	2,417	8	63	69	100	95	97	97
36/37	109	2,420	5	93	54	100	96	96	96
37/38	93	2,423	2	109	46	100	98	96	96
38/39	80	2,425	0	122	40	100	100	95	95
39/40	67	2,425	0	135	33	100	100	95	95

Note: The bolded row in the table indicates the suggested cut-off threshold.

confirm the POGQ on clinical samples. The current POGQ is short, comprehensive, and assesses problematic online gaming in different age groups with different data collection methods. Therefore, POGQ is an adequate tool for assessing problematic online gaming, facilitating future research, and helping legal authorities and health practitioners develop prevention and treatment programs.

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(*Appendix follows* →)

Appendix

Problematic Online Gaming Questionnaire Short Form (POGQ-SF)

Please read the statements below regarding *online gaming*. The questionnaire REFERS TO ONLINE GAMES exclusively, but we use the expression "game" in each statement for simplicity's sake. Please indicate on the scale from 1 to 5 to what extent, and how often, these statements apply to you!

	Never	*Seldom*	*Occasionally*	*Often*	*Always*
1. When you are not gaming, how often do you think about playing a game or think about how would it feel to play at that moment?	**1**	**2**	**3**	**4**	**5**
2. How often do you play longer than originally planned?	**1**	**2**	**3**	**4**	**5**
3. How often do you feel depressed or irritable when not gaming only for these feelings to disappear when you start playing?	**1**	**2**	**3**	**4**	**5**
4. How often do you feel that you should reduce the amount of time you spend gaming?	**1**	**2**	**3**	**4**	**5**
5. How often do the people around you complain that you are gaming too much?	**1**	**2**	**3**	**4**	**5**
6. How often do you fail to meet up with a friend because you were gaming?	**1**	**2**	**3**	**4**	**5**
7. How often do you daydream about gaming?	**1**	**2**	**3**	**4**	**5**
8. How often do you lose track of time when gaming?	**1**	**2**	**3**	**4**	**5**
9. How often do you get restless or irritable if you are unable to play games for a few days?	**1**	**2**	**3**	**4**	**5**
10. How often do you unsuccessfully try to reduce the time you spend on gaming?	**1**	**2**	**3**	**4**	**5**
11. How often do you argue with your parents and/or your partner because of gaming?	**1**	**2**	**3**	**4**	**5**
12. How often do you neglect other activities because you would rather game?	**1**	**2**	**3**	**4**	**5**

Preoccupation	*Immersion*	*Withdrawal*	*Overuse*	*Interpersonal conflicts*	*Social isolation*
1, 7	**2, 8**	**3, 9**	**4, 10**	**5, 11**	**6, 12**