Addiction

RESEARCH REPORT

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Online video game addiction: identification of addicted adolescent gamers

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ABSTRACT

Aims To provide empirical data-driven identification of a group of addicted online gamers. **Design** Repeated cross-sectional survey study, comprising a longitudinal cohort, conducted in 2008 and 2009. **Setting** Secondary schools in the Netherlands. **Participants** Two large samples of Dutch schoolchildren (aged 13–16 years). **Measurements** Compulsive internet use scale, weekly hours of online gaming and psychosocial variables. **Findings** This study confirms the existence of a small group of addicted online gamers (3%), representing about 1.5% of all children aged 13–16 years in the Netherlands. Although these gamers report addiction-like problems, relationships with decreased psychosocial health were less evident. **Conclusions** The identification of a small group of addicted online gamers supports efforts to develop and validate questionnaire scales aimed at measuring the phenomenon of online video game addiction. The findings contribute to the discussion on the inclusion of non-substance addictions in the proposed unified concept of 'Addiction and Related Disorders' for the DSM-V by providing indirect identification and validation of a group of suspected online video game addicts.

Keyword Compulsive internet use, internet addiction, latent class analysis, non-substance addiction, online video games, psychosocial health, video game addiction.

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INTRODUCTION

Studies have consistently demonstrated the existence of a small subgroup of video gamers that is seemingly 'addicted' to games [1–3]. Although video game addiction is not a new phenomenon [4], the introduction of an online component in the current generation of games has probably increased the size and scope of the problem. This online component in gaming led to the initiation of (private and public) treatment programmes targeting gaming addiction [5–7]. Consequently, there is increasing focus upon online games when studying video game addiction [8–11].

Both Korean and western researchers report specifically that Massive Multiplayer Online Role Playing Games (MMORPGs) are the main culprits in cases of online video game addiction [12–14]. In an MMORPG the player develops one or more characters (avatars) over time in a persistent virtual world. Examples include World of Warcraft, Age of Conan and Runescape. Typically, higher levels require players to cooperate to achieve goals. Moreover, MMORPGs cannot be completed: due to the regular introduction of new content it is practically impossible to finish all assignments. This places a considerable burden on the player's time, as they are required to continue playing to 'keep up' with the game. Research among a sample of World of Warcraft players identified a group of 10% who played an average of 63 hours per week and showed considerable negative symptoms [15]. Grüsser *et al*. sampled readers of an online gaming magazine in an online survey and found that 12% of those gamers fulfilled diagnostic criteria of addiction concerning their gaming behaviour [2].

These findings demonstrate the existence of a small subgroup of online gamers who can potentially be classified as 'online video game addicts'. This group is likely to have various psychological and social problems, as game overuse can be severely disruptive to school, work and 'real-life' social contacts [2,12,16]. Drawing parallels with the internet addiction literature, we hypothesize that this 'flight from reality' may be associated with negative self-esteem, depressive mood, social anxiety and/or loneliness [17–20]. However, the relationship between psychosocial health and online games is potentially more complicated, as social and psychological benefits from playing online games have also been reported [15,21,22]. Moreover, effects might differ based upon the psychological profile of the gamer, i.e. there may be a group of addicted heavy gamers who suffer as a result of their unbalanced life-style, and another group of heavy gamers who benefit from having multiple social environments. Given the former, and the fact that the vast majority of gamers do not report addictive tendencies [1], we hypothesize that a second group of heavy gamers is likely to exist. These non-addicted heavy gamers will probably not show negative psychosocial outcomes or addictive symptoms, or perhaps to a lesser extent.

Unfortunately, there is no consensus on an operational definition of video game addiction [11,23–25]. Despite the ongoing debate on diagnosis and definition, several methods are used to increase our understanding of game addiction. Researchers construct new scales to measure game addiction [1,3], avoid using standardized scales altogether [2] or approach the specific group of online games indirectly through more established measures of internet addiction [10,26]. Estimates of the size of the group of 'addicted gamers' are made subsequently by applying various cut-off points to scales measuring symptoms of video game addiction or internet addiction [1,3,27]. This results in a wide variety of estimates, depending upon the selected cut-off points and composition of the sample. In the absence of consensus on a definition, the absence of a gold standard with which to compare results and the lack of clinical studies using these instruments, these efforts are speculative at best.

The present study contributes to the debate on video game addiction by applying a different approach. It seeks to provide empirical, data-driven evidence for the assumed subgroup of addicted online video gamers, using two large-scale samples from the Dutch 'Monitor Study Internet and Youth'. Results provide a basis for data-based scale validation and cut-off scores. Identification of this group will be conducted through a combination of two indirect measures: game addiction severity and time spent on online gaming.

In the present study, internet addiction is thought to be an appropriate measure of online game addiction severity for several reasons. First, previous work by our group (utilizing an earlier Monitor Study sample) established cross-sectional and longitudinal relationships between online gaming and internet addiction, referred to as Compulsive Internet Use (CIU) [10]. Secondly, the latter study found low correlations between various internet activities and online video gaming among adolescents [28], in line with its immersive nature [29], thus confirming that online gaming is a monolithic activity for adolescents (these findings were replicated for the samples utilized in the present study). In combination with the inclusion of a measure of time spent on online gaming, this reduces the risk of misidentification (i.e. erroneously measuring addiction to various other applications). Consequently, the combination of a high score on CIU with many hours of online gaming per week is hypothesized to identify addicted online gamers. Note that we choose to utilize the term 'addiction' for the sake of consistency with other studies: the group is defined more precisely as heavy online gamers who score highly on criteria for non-substance addiction. These criteria are theorized to be applicable to online behaviour [1,3], also, see Measures [Compulsive Internet Use Scale (CIUS)].

From this, several research questions emerge. Can the two hypothesized groups of heavy online gamers (addicted and non-addicted) be identified using a data-driven approach? If so, how large are these groups? Finally, the present study explores the psychosocial correlates for the addicted versus the non-addicted heavy gamers, to further elucidate the theoretical relationship between game addiction and psychosocial wellbeing.

METHODS

Procedure

The Dutch 'Monitor Study Internet and Youth' provided data for the current study [10]. This ongoing longitudinal study uses stratified sampling to select schools for participation based upon region, urbanization and education level. Participating classes are included on a school-wide basis, and repeated yearly participation in the study is encouraged. Every year, participating adolescents complete a 1-hour questionnaire in the classroom, supervised by a teacher.

Written instructions are provided to the teacher, and questionnaires are returned in closed envelopes to ensure anonymity with regard to other students and teachers. Given the non-invasive nature of the study, passive informed consent is obtained from parents every year. More specifically, parents receive a letter with information about the planned questionnaire study on 'Internet use and well-being'. If parents do not agree with their child's participation they can inform the school coordinator and/or the researchers, in which case the child is excluded from participation. Children can refuse participation either by informing their parents or their teachers. Refusal by either parents or children rarely occurred.

Sample

The current study utilizes the 2008 (T1) and 2009 (T2) samples of the Monitor Study. Total response rate was

Table 1 Demographic information on the subsamples.

	Full sample		*Online gamers*		*Online gamers, cohort*
	T1	*T2*	*T1*	*T2*	*T1–T2*[a]
Participating schools	12	10	12	10	8
Overall sample size (*n*)	4559	3740	1572	1476	467
Gender (% boys)	49%	52%	82%	81%	90%
Dutch ethnicity (%)	78%	78%	78%	80%	80%
Higher education level (%)	66%	62%	64%	58%	62%
Average age (years); mean (SD)	14.35 (1.18)	14.34 (1.04)	14.21 (1.12)	14.24 (1.01)	13.76 (0.79)

[a]Values for T1 are reported. SD: standard deviation.

79% at T1, and 83% at T2. Non-response is mainly attributable to entire classes dropping out due to internal scheduling problems on schools; 13% of all classes did not return any questionnaires at T1 and 12% did not return questionnaires at T2. For the remaining classes, the average per class response rate was 89% at T1 and 92% at T2. Twelve secondary schools participated in the study at T1 and 10 secondary schools participated at T2. Of these schools, eight participated in both years.

Given the aim of the study, i.e. identification of a group of online gamers, the full sample is restricted to a subsample of online game players for both T1 (35%, $n = 1572$) and T2 (40%, $n = 1476$). Secondly, a longitudinal subsample, namely a cohort of online gamers who were included in both samples, can be identified between T1 and T2 ($n = 467$). Analyses in the present study span the first four classes of Dutch secondary school (average per year ages of 13, 14, 15 and 16 years, respectively). Table 1 presents demographic information on the subsamples for gender, ethnicity (Dutch/non-Dutch), higher secondary education (i.e. preparatory college and pre-university education) or lower secondary education (i.e. pre-vocational training), and average age.

Measures

Compulsive internet use

The 14-item version of the CIUS [30] was used to measure CIU, with its Dutch phrasing slightly adjusted for adolescents. This questionnaire (employing a five-point scale) covers several core components typical of behavioural addiction: withdrawal symptoms, loss of control, salience, conflict and coping (mood modification) [30], and includes questions such as 'Have you unsuccessfully tried to spend less time on the internet?' and 'Do you neglect to do your homework because you prefer to go on the internet?' The CIUS showed good validity [30] and internal reliability [30–32], and showed good reliability in the current samples (Cronbach's $\alpha = 0.88$ at both T1 and T2).

Weekly hours online gaming

Hours per week spent on online gaming were calculated by combining results from two questions (answers on a five-point scale) measuring days per week of online gaming [ranging from 'never', '1 day per week or less', '2/3 days per week', '4/5 days per week', to '(almost) daily'], and a seven-point scale measuring average hours of use on a gaming day (ranging from 'don't use', 'less than 1 hour', '1–2 hours', '2–4 hours', '4–6 hours', '6–8 hours' to '8 hours or more'. These questions were recoded to an interval scale and multiplied to obtain an approximation of number of hours per week. Note that although 'online game playing' includes more than just MMORPGs, an open question in the Monitor Study revealed that MMORPGs and First Person Shooters (shooting games utilizing a first person perspective, i.e. Call of Duty or Counterstrike) were the most popular types of online game [33].

Psychosocial outcome measures

The psychosocial measures in the present study were: the Rosenberg's Self-Esteem Scale [20,34], the UCLA Loneliness Scale [35,36], the Depressive Mood List [37–39] and the Revised Social Anxiety Scale for Children [40–42]. These scales have been used in Dutch studies and demonstrated good reliability in the past [32,43] and in the current samples (Cronbach's $\alpha > 0.80$). For all four scales, a higher score indicates more reported problems. To facilitate comparison between the scales, the present study reports standardized results.

Statistical analyses

Latent class analysis

Mplus 5.1 was used to perform a latent class analysis (LCA) [44]. LCA is an example of a mixture modelling technique used to identify meaningful groups of people (classes) that are similar in their responses to measured variables [45]. In the present study, these groups were based on scores for the variables CIU and Weekly Hours Online Gaming.

The present study used LCA in an exploratory manner, aiming to establish the presence of a (small) subgroup of addicted online video gamers. Besides fitting with this theoretical expectation, goodness-of-fit indices should be used to select a model of sufficient quality [46]. Two kinds of indices are used: measures of parsimony of the model and statistical tests to evaluate if the k + 1 solution is superior to a k class solution [47]. The preferred measure of parsimony is the Bayesian information criterion (BIC) [48], as shown in simulation studies [45,49]. Lower BIC values indicate a more parsimonious model. Statistical evaluation of model improvement was performed with the bootstrap likelihood ratio test (BLRT) [45]. Significant values for the BLRT indicate that the tested model (k) is superior to the previous model (k – 1). After selecting a solution (see Results), identified class membership was transferred to SPSS version 17 to examine longitudinal transition.

The data were standardized to facilitate interpretability and comparability of classes (groups). Standardized psychosocial correlates were explored through a Wald χ^2 test for mean equality of potential latent class predictors [50], followed by *post-hoc* tests to test for between-class differences. This test has the advantage of taking the probabilistic nature of class membership into account, leading to less biased estimates.

Table 2 Bayesian information criterion (BIC) values and entropy for different latent class analysis models.

	T1 (n = 1572)		*T2 (n = 1476)*	
Classes	*BIC*	*Entropy*	*BIC*	*Entropy*
1	8941	—	8399	—
2	8071	0.977	7437	0.981
3	7594	0.968	6973	0.967
4	7221	0.965	6619	0.967
5	6690	0.972	6264	0.962
6	6353	0.989	5847	0.989

RESULTS

Latent class identification

Table 2 gives the model fit indicators for the 1–6 latent class models when identifying classes on the basis of CIU and Weekly Hours Online Gaming (Online Gaming). The BLRT consistently reports significant outcomes ($P < 0.001$) and BIC values are decreasing, indicating that each model is superior to the previous one. Entropy values are consistently high, indicating good classification quality.

A subgroup of assumed addicted gamers, with a higher amount of weekly online gaming and a higher score on CIU, is identified from the three-class solution onwards. This group remains stable in the four- and five-class solutions for both time-points (T1: $n = 56$; $n = 1572$; T2: $n = 75$, $n = 1476$). For the three-, four- and five-class solutions the relationship between CIU and online gaming seems to have a linear nature: classes are distributed along a straight line, where increases in online gaming are related linearly to simultaneous increases in CIU. The six-class model breaks this trend, as it splits the class with the highest CIU into two groups. Table 3 shows that the first group (class five) has a moderate increase in hours spent on online gaming, while CIU scores remain stable or drop. Thus, class five identifies the non-addicted heavy gamers. The second group shows a moderate increase in hours spent on online gaming, accompanied by a disproportionate increase in CIU. As this group (class six) identifies the

Table 3 Six latent class model, standardized and unstandardized results for the six classes.

	T1						*T2*					
			Online gaming (hours per week)		*Compulsive internet use scale*				*Online gaming (hours per week)*		*Compulsive internet use scale*	
Class	*n*	*%*	*Z-score*	*hours/week*	*Z-score*	*CIUS*	*n*	*%*	*Z-score*	*hours/week*	*Z-score*	*CIUS*
1	813	51.7%	–0.65	1.8	–0.21	1.7	773	52.4%	–0.64	1.7	–0.22	1.7
2	421	26.8%	–0.01	9.3	–0.04	1.8	374	25.3%	–0.05	9.3	0.00	1.8
3	198	12.6%	0.87	19.7	0.36	2.1	179	12.1%	0.77	19.8	0.23	2.0
4	84	5.3%	1.94	32.5	0.56	2.2	75	5.1%	1.76	32.5	0.48	2.1
5	18	1.1%	3.04	45.5	0.30	2.0	27	1.8%	2.76	45.5	0.51	2.1
6	38	2.4%	3.86	55.3	1.75	2.9	48	3.3%	3.52	55.3	1.65	2.8
Total	1572						1476					

CIUS: Compulsive Internet Use Scale.

Table 4 Six class model classes compared on standardized psychosocial outcome measures within T1 and T2.

		Depressive mood		Loneliness		Social anxiety		Negative self-esteem	
	Class	T1	T2	T1	T2	T1	T2	T1	T2
T1	1	0.05	0.02**	0.06	−0.01*	0.00	0.00	0.03	0.04**
	2	−0.11	−0.02**	−0.12*	−0.05*	−0.03	−0.02	−0.07	−0.11***
	3	0.00	−0.14	0.08	−0.11	0.06	−0.06	−0.03*	−0.16
	4	−0.08	−0.03	−0.16**	0.04	−0.06	0.11	0.04	0.03*
	5	−0.05	−0.21**	−0.37	0.41	0.02	0.01	−0.15	0.13
	6	0.31	0.47	0.16	0.67	0.13	0.27	0.39	0.67
	χ^2	9.89	11.42	19.96	10.59	1.70	2.90	8.62	20.56
	P	0.078	0.044	0.001	0.06	0.889	0.715	0.125	0.001

Comparisons are made between group six and the other groups (*$P < 0.05$; **$P < 0.01$; ***$P < 0.001$). Standardized values are reported for all four psychosocial outcome measures. Higher values indicate more reported problems on the respective scale.

Table 5 Latent class membership and longitudinal persistence.

		T2						
		1	2	3	4	5	6	n
T1	1	60.6%	24.6%	10.3%	3.4%	0.5%	0.5%	203
	2	37.5%	38.2%	14.6%	6.3%	0.0%	3.5%	144
	3	25.3%	25.3%	34.2%	11.4%	1.3%	2.5%	79
	4	17.2%	27.6%	17.2%	24.1%	10.3%	3.4%	29
	5	0.0%	16.7%	16.7%	16.7%	16.7%	33.3%	6
	6	0.0%	16.7%	0.0%	0.0%	33.3%	50.0%	6
	n	202	135	75	33	8	14	467

hypothesized group of addicted online gamers, the six-class model is selected as final model.

Table 3 gives the standardized and unstandardized means for this six-class model, revealing consistent class identification in both years. Unstandardized results are reported to illustrate the actual number of hours played and to support future development of cut-off scores for the CIUS. This result can be attributed partially to repeated measurement. However, the longitudinal cohort represents approximately 30% of the respective samples (T1 and T2). From this, it is assumed that the classes are both stable and replicable. When the data are weighed against national statistics [51] (using learning year, region, gender, ethnicity and education level) to obtain a nationally representative estimate for the Netherlands, the percentage of addicted heavy online gamers (i.e. class six) translates to 1.6% of the entire population aged 13–16 years in the Netherlands at T1 and 1.5% at T2.

Examination of psychosocial correlates

Table 4 presents the six-class model through comparison of standardized psychosocial variables across the various classes. Significant overall differences were found for depressive mood (T2, $P < 0.05$), loneliness (T1, $P < 0.01$) and negative self-esteem (T2, $P < 0.01$). Visual inspections of the table shows overall higher mean scores for all four psychosocial variables in class 6 (the most addicted group). *Post-hoc* tests comparing the most addicted class (6) with the other classes revealed several significant differences for depressive mood (T2), loneliness (T1, T2) and negative self-esteem (T1, T2). Focusing specifically upon the two groups of heavy gamers (addicted, class 6 and non-addicted, class 5), only one significant difference was found, i.e. at T2 the addicted gamers were more depressed than the heavy gamers.

Longitudinal persistence of class membership

Table 5 presents longitudinal (year-to-year) transitions for the various classes. Results show that, apart from the first class, retention for the sixth class is higher than for other classes. In this cohort, although the absolute number of people in the sixth class is low, results indicate that half the addicted online gamers at T1 ($n = 6$) are still addicted at T2 ($n = 3$).

DISCUSSION

The present study has identified successfully two distinct groups of gamers: one group of addicted heavy online gamers and another group of heavy but non-addicted online gamers, thus confirming our main hypothesis. The addicted heavy online gamers differed only slightly from the non-addicted heavy gamers (and various other groups) in terms of psychosocial health. However, some of these addicted gamers showed persistence over time, i.e. half the addicted online gamers were still addicted 1 year later.

Two large-scale samples from a nationally representative study were used to classify online gamers with CIU. Using a data-driven approach, analyses showed the existence of six distinct groups within the data. The vast majority of online gamers (95%) are located in four groups, which show a linear increase in CIU as the hours per week of gaming increase. The fifth and sixth groups break this trend. The fifth group is identified as a group of heavy online gamers who play many hours per week, but show stability or even a drop in addiction (2008) when compared to the previous groups. This group of non-addicted heavy online gamers is relatively small (about 1–2% of the online gamers, see Table 3).

The sixth group, which contains about 3% of the online gamers in the period 2008/09, spends many hours on online gaming and reports more symptoms of CIU than other groups. Thus it is identified as a group of addicted heavy online video gamers. These numbers translate to an average national estimate of 1.5% (2008) and 1.6% (2009) of addicted heavy online gamers among all Dutch adolescents in the first four classes of secondary education (aged 13–16 years). These adolescents report an average of 55 hours per week on gaming.

Subsequently, psychosocial correlates were examined for the addicted online video gamers. Visual inspection of the data shows higher scores on depressive mood, loneliness, social anxiety and negative self-esteem for addicted online gamers compared to other online gamers. However, *post-hoc* testing revealed that most of the actual bilateral relationships are non-significant from the perspective of the addicted online gamers. When compared to non-addicted heavy gamers, only one significant difference was found: in 2009 the addicted heavy gamers were more depressed than the non-addicted heavy gamers.

These ambiguous results illustrate the complexity of the relationship between online video game use, online video game addiction and psychosocial health. Especially in the case of outcome variables with a strong social element, such as loneliness and self-esteem, video gaming may well have a dualistic effect. First, it expands the horizon of the gamer by offering a second environment in which to experiment [52] and, later on, it may constrain social options in 'real life' when the second life starts to overshadow the first [8]. In this way, depressive symptoms, loneliness and negative self-esteem might decrease for some gamers as they find refuge in online games; on the other hand, these correlates may increase for others because relying exclusively on online relationships may fail to provide the full spectrum of social contacts and support the gamer's needs in real life. This hypothesis fits well with earlier theoretical work on 'problematic internet use' by Caplan [17,18]. Further examination of these complex relationships in the case of online gaming might benefit from using statistical methods focusing upon modelling, such as structural equation modelling. Clinical studies will need to be utilized to establish the actual harm and treatability of the problems associated with 'online video game addiction'.

The identification of a small group of addicted heavy online gamers supports future efforts to develop and validate questionnaire scales aimed at measuring the phenomenon of 'online video game addiction'. It also confirms the existence of the group through an alternative approach, thereby confirming earlier results for the subgroup of online gamers [1,3]. Additionally, it provides a basis on which to establish empirically supported cut-off points for scales aiming to measure online video game addiction. Although an addicted group of gamers was found, substantial caution should be exercised before the creation of a new 'disorder', due to the modest impairment and longitudinal persistence.

The current study has several strengths. It provides a data-driven prevalence estimate for 'video game addiction' in the Netherlands, based upon two large-scale samples. Additionally, it provides some of the first longitudinal data on the development of this phenomenon over time. However, the study also has some limitations. First, the study uses self-report data, which is known to carry the risk of bias [53]; this should be taken into account when comparing estimates with external outcome variables, such as the number of people reporting for clinical treatment with game addiction as the main complaint. Secondly, the 'hours per week' variable was the result of a multiplication and might be affected by ceiling effects; as such, it should be viewed as an estimate and not as an absolute value. Thirdly, clinical measures were restricted to psychosocial measures and a measure of addiction: future research might benefit from the inclusion of specific clinical measures of, for example, hyperactivity and mania. Finally, different types of online video games are available. Whereas 'online video games' are an advancement of the unified 'video games' approach, future research may benefit from further differentiation, e.g. by distinguishing online First Person Shooter games from online Role Playing Games.

In summary, this study confirms the existence of a small percentage (3%) of addicted online gamers. This group represents approximately 1.5% of all children aged 13–16 years in the Netherlands. Although these gamers report addiction-like problems, relationships with decreased psychosocial health were less evident. While survey-based data cannot determine the exact clinical nature of game addiction, the present findings contribute to the discussion on the proposed unified concept of 'Addiction and Related Disorders' (which includes non-substance addictions) in the DSM-V [54].

Declarations of interest

None.

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