Neurodevelopmental Traits and Longitudinal Transition Patterns in Internet Addiction:

A 2-year Prospective Study

（子どものインターネット依存状態の変化とその状態変化に関わる発達特性）

申請者　　弘前大学大学院医学研究科
総合医療・健康科学領域
精神・神経分子科学教育研究分野

氏　　名　　廣田　智也

指導教授　　中村　和彦

Abstract

Despite increasing attention to internet addiction (IA) in both clinical practice and research, our understanding of longitudinal changes of IA status is limited. In the present study, we employed latent transition analysis to investigate patterns of transitions and the stability of IA status among 5483 students (aged 9- 12 years) over the two-year study periods. Additionally, we examined whether neurodevelopmental traits predicted certain transition patterns. The stability rate of IA class membership and the conversion rate from non-IA to IA status across the 2 years were 47% and 11%, respectively. The regression model revealed that autistic traits predicted the persisting IA pattern and that inattention traits predicted both the persisting and converting (from non-IA to IA status) patterns.

Key words: internet addiction, longitudinal study, latent class analysis, latent transition analysis, neurodevelopmental traits

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Introduction

Internet addiction (IA) has been gaining more attention recently, in both clinical practice and research, particularly after the inclusion of Internet Gaming Disorder in the Diagnostic and Statistical Manual of Mental Disorders, fifth edition (DSM 5), as a condition for further study (Jorgenson, Hsiao, and Yen 2016; Spada 2014). The World Health Organization recently released the 11th revision of the International Classification of Diseases (ICD-11), and the inclusion of Gaming Disorder as an official diagnosis has accelerated its popularity even among nonprofessionals. Prevalence rates vary by study; however, it is reported to be approximately 4% in general population samples (Durkee et al. 2012; Kaess et al. 2014; Mak et al. 2014). Existing cross-sectional studies indicate that IA is associated with challenges in interpersonal relationships, decreased well-being, poor academic performance, and psychopathologies such as anxiety and depression (Yücens and Üzer 2018).

The majority of the findings mentioned above have been from cross-sectional studies, limiting our understanding of how IA symptoms and status change over time. A few longitudinal studies have reported changes in the severity of IA over time using scores of certain scales, such as the Internet Addiction Test (IAT) [(Lau, Gross, et al. 2017; Lau, Wu, et al. 2017). One study revealed that although more than half of adolescents with IA remitted over the 12-month study period, the rest continued to show elevated scores on the IAT and meet the criteria for IA (Lau, Wu, et al. 2017). However, little is known about what subgroups of these individuals persist in or develop problematic internet use over time. Identifying these groups is of clinical importance in order to provide interventions for certain subgroups of students given the negative outcomes associated with IA.

A higher prevalence of IA has been reported in individuals with neurodevelopmental disorders (NDDs) such as autism spectrum disorder (ASD) and attention deficit hyperactivity disorder (ADHD), compared with individuals with typical development (So et al. 2017). Additionally, previous studies have reported associations of IA with ASD traits (Liu et al. 2017) and ADHD traits (Wang et al. 2017) in a general population sample, indicating that these disorders and traits can be risk factors for IA. Cross-sectional studies have reported that NDD traits, such as seeking immediate reward to reduce boredom (ADHD) and restricted interest and repetitive behaviors (ASD), are more likely to lead to IA in individuals with NDDs or NDD traits (Gwynette, Sidhu, and Ceranoglu 2018; Wang et al. 2017). These findings suggest interventions targeting these disorders and traits may reduce the severity of IA or even prevent the development of IA. Yet, to our knowledge, no studies have examined how these neurodevelopmental traits impact longitudinal changes in IA.

The primary aim of this study was to examine the stability or instability of student internet use over a 2-year period in a general population sample. More specifically, we investigated which subgroups of students would maintain the same degree of internet use and which would move to different degrees within the study period. To this aim, we examined longitudinal patterns of subgroup transitions between the first study year and the second, the second and the third, and the first and the third, using latent transition analysis. The secondary aim of this study was to investigate whether certain neurodevelopmental traits could predict certain longitudinal patterns of the movements among the subgroups of students. Specifically, we investigated whether neurodevelopmental traits related to ASD and ADHD measured at the study baseline could predict the following two transition patterns: the persisting IA pattern and the converting IA pattern (i.e., newly developed IA during the study period).

Methods

Study setting and participants

We conducted a community-based survey annually from September 2016 to September 2018 and prospectively followed students attending national or public school in Hirosaki City, Japan. The students were in fourth to seventh grade (equivalent to 9-12 years of age) at the start of the study (see Table 1). We defined the 2016, 2017, and 2018 time points as Time 1 (T1), Time 2 (T2), and Time 3 (T3), respectively. At each time point, we mailed letters containing information on the study to the parent or guardian of each student. Students whose parent or guardian did not consent to their participation in the study were excluded. The students were briefed about the purpose of the survey and completed the questionnaire in the classroom. The protocol of the study was approved by the Committee on Medical Ethics of Hirosaki University (IRB# 2015-055), and the present study was performed in accordance with the ethical standards laid down in the 1964 Declaration of Helsinki and its later amendments.

Measurements and procedure

We used the Young Diagnostic Questionnaire (YDQ) for the assessment of IA. The YDQ is an eight-item questionnaire with a binary “yes” or “no” response format (Young 1998). The eight items are based on the criteria for pathological gambling in the DSM-IV. According to Young, who developed the YDQ, participants who answer “yes” to five or more of the questions could be classified as having IA (Young 1998). Beard and Wolf suggested that the first five criteria (preoccupation, tolerance, inability to reduce internet use, restlessness or moodiness when reducing usage, and excessive time online) and at least one of the latter three (adverse consequences, concealing internet use, and escapism) should be met for a diagnosis of IA using the YDQ (Beard and Wolf 2001). In this study, we defined IA status base on the findings from latent class analysis (LCA), the definition of which was consistent with that suggested by Beard and Wolf. The details of the LCA findings will be described below.

Two questionnaires were used to measure neurodevelopmental traits: the Autism Spectrum Screening Questionnaire (ASSQ; (Ehlers, Gillberg, and Wing 1999) and the Attention-Deficit/Hyperactivity Disorder Rating Scale (ADHD-RS; (DuPaul et al. 1998). Both questionnaires were administered to the parent or guardian of the participating students. The ASSQ is a screening tool to identify ASD in school-aged children that consists of 27 items rated on a 3-point scale. Of the 27 items, 11 are on social interactions, 6 are on communication problems, and 5 are on restricted and repetitive behavior. The remaining items pertain to motor clumsiness and other associated symptoms. The ASSQ was translated into many languages, including Japanese, and its psychometric properties were validated in a general population sample (Ito et al. 2014). The ADHD-RS was developed to measure two features of ADHD: inattention (nine items) and hyperactivity-impulsivity (nine items). The Japanese-version of the ADHD-RS was validated in a general population sample (Ohnishi et al. 2010).

In this study, students filled out the YDQ annually (in 2016, 2017, and 2018 [T1, T2, and T3]). The ASSQ and the ADHD-RS were administered at T1 alone. Full information maximum likelihood was used for missing data; students with missing data for all items of the YDQ were excluded from the data analyses.

Analytic plans

We performed latent transition analysis (LTA) to examine patterns of transitions and stability among the subgroups over 2 years. LTA is a longitudinal extension of LCA, which is a person-centered approach allowing for identifying similar patterns of responses to questionnaire items (YDQ items in the present study) and thereby identifying unobservable (i.e., latent) subgroups of individuals who are homogenous in their baseline clinical presentation (Collins and Landa 2010). LTA is a model-based clustering methodology for categorical data that imposes *autoregressive* relations between latent class variables at each time point. We conducted LTA using the following steps, which are recommended to prevent changes in latent classes at each time point (Nylund-Gibson et al. 2014): 1) determining LCA model fit at each time point, 2) testing measurement invariance to determine whether a measurement model remains consistent over time, 3) examining second-order effect, and 4) specification of the final LTA model.

LCA models of student internet use were independently specified using eight items of the YDQ as indicators. We performed cross-sectional LCAs for each time point (T1, T2, and T3). Class enumeration started with a one-class solution, followed by an exploration of additional models with more latent classes (two-class model, then three-class model, for example). The fit indices used included the Akaike information criterion (AIC; (Akaike 1987), Bayesian information criterion (BIC; (Schwarz 1978), and Vuong-Lo-Mendell-Rubin likelihood ratio test (VLMR-LRT; (Lo, Mendell, and Rubin 2001). Entropy, an indicator of model quality, was also reported; entropy with values approaching 1 indicates clear delineation of classes (Celeux and Soromenho 1996). To ensure that the models converged on global rather than local solutions, 500 random sets of starting values and 50 final stage optimizations were used. The rest of the steps taken for LCA is described in **Supplementary Data 1**.

In this study, we categorized longitudinal changes in student internet use into the following three groups: the pattern where students stay in IA status (the persisting pattern), the pattern where students move from non-IA status to IA status (the converting pattern), and other patterns (including the persisting non-IA pattern and the remitting to non-IA pattern). Based on the LCA findings that revealed three distinct classes (detailed described in Results), students belonging to the pathological internet use (PIU) were defined to have IA, and those belonging to the excessive internet use (EIU), and normative internet use (NIU) classes were defined to not have IA in the present study. The PIU class membership is characterized by several signs of behavioral addiction, such as preoccupation, tolerance, failure to control internet use, withdrawal symptoms, and internet use to relieve dysphoria. The EIU class membership has much fewer signs than the PIU class membership and is characterized by failures to control internet use and longer duration of internet use than intended. The NIU class membership is characterized by no pronounced indication of the signs listed above. To determine which neurodevelopmental traits could predict persisting and converting patterns of IA, we performed multinomial logistic regression analysis using patterns of transitions among subgroups as dependent variables and neurodevelopmental traits (ASSQ total score, ADHD-RS inattention subscale score, ADHD-RS hyperactivity/impulsivity subscale score) as independent variables. Sex and age/grade were also entered as independent variables into the regression model.

All analyses were conducted using Mplus version 7.4 (Muthén and Muthén, Los Angeles, CA, USA) and SPSS version 22.0 (IBM Corporation, Armonk, NY, USA).

Results

Table 1 summarizes the characteristics of the participating students at T1. A total of 5483 students (50.4% boys and 49.6% girls) participated in the study in 2016. The number of students who agreed to participate in the study and who were eliminated from data analyses due to missing data (i.e., students who did not answer all YDQ items) at each time point is summarized in the **Supplementary Data 2**. The retention rates at T2 and T3 were 98.1% and 93.4%, respectively.

Table 2 lists the information used to assess the fit of each LCA model. After carefully comparing fit indices (BIC and p-value of VLMR-LRT) for each time point and examining each class solution, we selected the three-class solution as the optimal model for T1, T2, and T3 (please see **Supplementary Data 3** for further explanations about this LCA step). Each class membership was defined as PIU, EIU, and NIU, respectively. **Figure 1** depicts the three-class model at T1, T2, and T3, where the X-axis represents the item number of the YDQ and the Y-axis represents the probability of answering "yes" to the given item.

Table 3a presents the transition probabilities for the first-order effects (the effect of status at T1 on status at T2 or the effect of status at T2 on status at T3) of the final LTA model. The NIU class demonstrated the highest stability for both T1 to T2 and T2 to T3 (81% and 79%, respectively), whereas the lowest stability was demonstrated by the PIU class for both T1 to T2 and T2 to T3 (64% and 65%, respectively). The transitions from NIU to PIU and from EIU to PIU were 2% and 8% for T1 to T2, respectively, and 2% and 6% for T2 to T3, respectively. **Table 3b** shows the transition probabilities for the second-order effect (the effect of status at T1 on status at T3) of the final LTA model. The stability of class membership from T1 to T3 was 68% for NIU, 76% for EIU, and 47% for PIU. The transition rates from NIU to PIU and from EIU to PIU were 3% and 8%, respectively.

Table 4a summarizes the associations between the longitudinal persisting pattern and neurodevelopmental traits, gender, and sex across 1 year (i.e., T1 to T2 and T2 to T3) and 2 years (i.e., T1 to T3). Multinomial logistic regression analysis revealed higher ASSQ total score, higher ADHD-RS inattention subscale score, and higher school grades (sixth and seventh grades compared with fourth grade) to be significant predictors of the persisting pattern for both T1 to T2 and T2 to T3. A higher ASSQ total score and higher school grades were significant predictors of the persisting pattern for T1 to T3. Sex was not found to be a predictor of this pattern. **Table 4b** summarizes the associations between the longitudinal converting pattern and neurodevelopmental traits, gender, and sex across 1 and 2 years. A higher ADHD-RS inattention subscale score alone was a significant predictor for the converting pattern for both T1 to T2 and T2 to T3. A higher ADHD-RS inattention subscale score was the only significant predictor for the converting pattern from T1 to T3. Sex was not found to be a predictor of this pattern.

Discussion

We conducted a 2-year longitudinal study that tracked the patterns of internet use in elementary and junior high school students. In this study, we identified three distinct subgroups of students based on their internet use, as measured with the YDQ at each time point using LCA, a structural equation modeling technique. These subgroups were the PIU group, the EIU group, and the NIU group, among which students belonging to the PIU group were considered to have IA. Using LTA, an extension of LCA, we identified transition patterns of class membership across one study year and across two study years.

In this study, the PIU subgroup in the three-class model supported by fit indices through LCA was considered to have met the criteria for IA defined by Young and the modified criteria proposed by Beard and Wolf. The percentages of students belonging to the PIU class at T1, T2, and T3 were 5.6%, 8.2%, and 6.7%, respectively. The prevalence of IA (the PIU class) in the present study was slightly higher than that reported in other studies (4%-5% in European and Asian studies) [3,5], this difference in findings is likely due to differences in participants' ages, the measurements used, and how IA was defined.

The transition probability from IA to non-IA across one study year was 36% (T1 to T2) and 35% (T2 to T3), respectively. The transition probability from IA to non-IA across the two study years was 53%. These transition probabilities do not greatly differ from that reported in a previous study conducted in Hong Kong, in which 45.9% of students aged 12-15 years who met the criteria for IA (based on the total score on the Chen Internet Addiction Scale) at baseline showed remission to non-IA at 1-year follow-up [9]. To our knowledge, students in the present study did not receive any specific interventions for IA during the study years. Therefore, our findings using LTA supported those of the above-mentioned Hong Kong study that indicated that certain students with IA could remit even without interventions or treatments. On the other hand, our findings also indicated that nearly half of the students with IA maintained the same status of internet use across the two study years. Transition probabilities from non-IA status (NIU and EIU) to PIU were relatively small (10% from T1 to T2, 8% from T2 to T3, and 11% from T1 to T3). These findings were similar to that reported in another study conducted in Hong Kong, where the incidence of IA conversion rate within the 1-year study period was 11.5% [8]. Our findings, together with ones from existing longitudinal studies, related to the temporal stability and instability of IA would be of clinical importance in deepening our understanding of the natural course of IA status and determining the necessity of timely interventions. Our findings also support the proposal by the DSM-5 that a past-year timeframe of symptoms needs to be included in the assessment of internet gaming disorder (Petry et al. 2014). Although factors accounting for the conversion from IA to non-IA were not examined in the present study, it is possible that the child's social functioning and well-being at baseline could predict this conversion pattern from IA to non-IA. As recent research has supported the efficacy of positive psychology interventions enhancing positive emotions and promote social relations of individuals with IA (Khazaei, Khazaei, and Ghanbari-H. 2017), future research including these variables is needed.

The higher ASSQ total score predicted the persisting pattern of IA in the present study. The persistence of behavioral patterns related to IA could be due to the impairment in social communication and interaction, which is a core trait of ASD. An earlier cross-sectional study has reported higher rates of electronic use, particularly problematic video games that require little social engagement, in individuals with ASD compared to typically developing individuals given the nature of their poor social skills (So et al. 2017; Mazurek et al. 2012). As ASD symptoms and traits are generally stable over time (Bieleninik et al. 2017), it is also possible that challenges in social communication and interaction maintain the stability of IA over time. Contrary to this, another cross-sectional study has revealed that video game use in individuals with ASD was not associated with core symptoms of (Mazurek et al. 2012). Thus, future studies with longitudinal design need to replicate our findings and examine the association of core ASD symptoms with the persistence of IA. Other ASD traits, such as repetitive and restricted interests and behaviors may contribute to the persisting pattern of IA given the compulsive nature of internet addiction. Individuals who have these traits may want to be perseverative on certain online activities, maintaining their IA status due to their cognitive rigidity. Examining whether certain ASD traits, rather than overall ASD traits, predict longitudinal transition patterns of internet use would be meaningful to provide problem-specific interventions, such as social skills groups and cognitive flexibility training. As the ASSQ used in the present study does not have subscale scores established by factor-analytic studies, future research using other scales such as the Social Communication Questionnaire (Rutter, Bailey, and Lord 2003) and Social Responsiveness Scale (Constantino and Gruber 2005) should be conducted.

Our findings also revealed that the ADHD-RS inattention subscale score predicted both persisting and converting patterns across 1 year (T1 to T2 and T2 to T3) and across 2 years. The predictive role of ADHD for the occurrence of IA was also found in a 2-year prospective study conducted in a general population sample of Taiwanese students (Ko et al. 2009). However, no subscale scores of the questionnaire used for the assessment of ADHD in the above study were available, prohibiting further analysis to examine whether the occurrence of IA could be predicted by the overall ADHD symptoms or by certain subtypes of ADHD. Another longitudinal study conducted in Taiwan reported that ADHD-related symptoms, including, inattention, hyperactivity, and impulsivity, measured at baseline predicted students' internet addiction in the 3-month follow-up (Chen, Chen, and Gau 2015). However, multiple analyses did not support this prediction model and instead revealed that poor academic performance was predictive for internet addiction. Therefore, it is probable that our finding that inattention symptoms predicted certain IA transition patterns could also be attributable to poor academic performance. Future studies can benefit from obtaining more variables to investigate the mechanism that could account for the contribution of inattention symptoms to persisting and converting transition patterns.

Our findings revealed that older students (sixth and seventh graders) were more likely to demonstrate a persisting pattern of IA across the 1-year study period. This finding could be attributable to the fact that older students have greater accessibility to the internet and higher smartphone ownership rates in Japan (Cabinet Office, Government of Japan: https://www8.cao.go.jp/youth/youth-harm/chousa/net-jittai_list.html). Although it is reported that the prevalence of IA is higher in older school-aged children than younger school-aged children (Takahashi et al. 2018), no studies have examined how age can contribute to persistent pathological internet use over time. Further studies replicating our findings are needed to determine the necessity of prompt interventions in junior high school/middle school students once they are identified as having IA in order to prevent the persistence of IA problems.

This study has some limitations. First, we did not obtain any socioeconomic data except for students' sex and age/school grade. Provided that previous studies reported associations of problematic internet use with family functioning and parenting style (Chen, Chen, and Gau 2015), future studies should include these variables in their analysis. Second, neurodevelopmental traits were measured only once at baseline, precluding analyses on longitudinal interactions between neurodevelopmental traits and IA problems. Third, our findings may not be generalizable to populations where individuals are diverse in language, race, and culture.

Despite these limitations, this study has several strengths. One major strength of the study is that, compared with the approaches commonly used in other studies in this area (e.g., using the total number of positive scale items to classify the severity of internet use), we used LCA, a model-based approach that provides statistically refined findings. Additionally, LTA, an extension of LCA, is a person-centered approach, which can provide us with a better understanding of how subgroup populations transition from one status to another and how they maintain their status. Other strengths include large sample size, high retention rates, a longitudinal study design, and the use of internationally validated scales for the measurement of neurodevelopmental traits.

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Table 1. Characteristics of participating students at the time of the study entry

Grade (Age: years)	4^{th} (9 - 10)	5^{th} (10 - 11)	6^{th} (11 - 12)	7^{th} (12 - 13)	All grades (9 - 13)
Total (N)	1339	1336	1351	1457	5483
Male (%)	49.9	50.5	48.7	52.3	50.4
Female (%)	50.1	49.5	51.3	47.7	49.6
ASSQ total score					
mean (SD)	4.5 (5.7)	4.3 (5.6)	3.9 (4.8)	4.0 (5.1)	4.2 (5.3)
range	0 - 36	0 - 41	0 - 41	0 - 39	0 - 41
ADHD-RS total score					
mean	6.6 (7.1)	5.7 (6.6)	4.6 (5.9)	4.6 (5.5)	5.4 (6.3)
range	0 - 44	0 - 49	0 - 39	0 - 36	0 - 49

ADHD-RS = ADHD Rating Scale, ASSQ = Autism Spectrum Screening Questionnaire

Table 2: Class determination at each time point

Model	N of classes	Log likelihood	AIC	BIC	VLMR-LRT (p value)	Entropy
Year 2016 (T1)	1	-14649.351	29314.702	29367.498	-	1
(n = 5429)	2	-12570.818	25175.636	25287.827	< 0.0001	0.80
	3	-12280.505	24613.011	24784.598	< 0.0001	0.78
	4	-12230.797	24531.582	24762.565	0.61	0.79
	5	-12199.937	24487.875	24778.253	0.0003	0.82
Year 2017 (T2)	1	-15622.757	31261.513	31314.171	-	1
(n = 5336)	2	-13648.443	27330.886	27442.784	< 0.0001	0.77
	3	-13341.333	26734.665	26905.803	< 0.0001	0.74
	4	-13287.707	26645.414	26875.792	< 0.0001	0.77
	5	-13270.057	26628.113	26917.732	0.21	0.72
Year 2018 (T3)	1	-15772.421	31560.842	31613.13	-	1
(n = 5095)	2	-14018.452	28070.905	28182.017	< 0.0001	0.73
	3	-13704.612	27461.224	27631.16	< 0.0001	0.73
	4	-13655.036	27380.072	27608.832	< 0.0001	0.71
	5	-13639.935	27365.546	27653.131	0.09	0.75

AIC = Akaike Information Criteria, BIC = Bayesian Information Criteria, BLRT = Bootstrap Likelihood ratio Test, VLMR-LRT = Vuong Lo Mendel Rubin LRT

Table 3a. Class transition from the year 2016 (Time 1) to the year 2018 (T3): first order effect

		T2		
		NIU	EIU	PIU
	NIU	0.81	0.17	0.02
T1	EIU	0.14	0.78	0.08
	PIU	0.15	0.21	0.64

		T3		
		NIU	EIU	PIU
	NIU	0.79	0.19	0.02
T2	EIU	0.09	0.85	0.06
	PIU	0.08	0.27	0.65

NIU = normative internet use, EIU = excessive internet use, PIU = pathological internet use

Table 3b. Class transition from the year 2016 (Time 1) to the year 2018 (T3): second order effect

		T3		
		NIU	EIU	PIU
	NIU	0.68	0.29	0.03
T1	EIU	0.16	0.76	0.08
	PIU	0.14	0.4	0.47

NIU = normative internet use, EIU = excessive internet use, PIU = pathological internet use

Table 4a. Predictors for the persisting pattern of internet addiction (numbers bolded if $p < 0.05$)

	β	SE	Wald	df	Sig.	Exp(β)	95% CI
T1 -> T2 (n = 4722)							
Sex	-0.13	0.14	0.77	1	0.38	0.88	0.66 - 1.17
School grade (4th grade as a reference)							
Grade 5	0.21	0.20	1.07	1	0.30	1.23	0.83 - 1.84
Grade 6	0.48	0.19	6.31	1	**0.01**	1.62	1.11 - 2.37
Grade 7	0.87	0.18	23.7	1	**< 0.001**	2.39	1.69 - 3.40
ASD traits (ASSQ total score)	0.05	0.01	14.8	1	**< 0.001**	1.05	1.02 - 1.08
Inattention (ADHD-RS subscale)	0.05	0.02	7.10	1	**0.008**	1.06	1.01 - 1.10
Hyperactivity/impulsivity (ADHD-RS subscale)	0.01	0.03	0.13	1	0.71	1.01	0.95 - 1.08
T2 -> T3 (n = 4722)							
Sex	-0.11	0.14	0.60	1	0.44	0.90	0.69 - 1.18
School grade							
Grade 5	0.16	0.20	0.66	1	0.42	1.17	0.80 - 1.72
Grade 6	0.52	0.18	7.94	1	**0.005**	1.68	1.17 - 2.41
Grade 7	0.81	0.17	21.5	1	**< 0.001**	2.24	1.59 - 3.14
ASD traits (ASSQ total score)	0.03	0.01	6.18	1	**0.01**	1.03	1.007 - 1.06
Inattention (ADHD-RS subscale)	0.07	0.02	13.6	1	**0.0002**	1.07	1.03 - 1.12
Hyperactivity/impulsivity (ADHD-RS subscale)	0.0007	0.03	0.0005	1	0.98	1.00	0.94 - 1.06
T1 -> T3 (n = 4716)							
Sex	- 0.19	0.18	1.16	1	0.28	0.83	0.58 - 1.17
School grade							

Grade 5	0.29	0.28	1.13	1	0.29	1.34	0.78 -2.30
Grade 6	0.75	0.26	8.24	1	**0.004**	2.11	1.27 - 3.52
Grade 7	0.84	0.26	1.06	1	**0.001**	2.30	1.39 - 3.81
ASD traits (ASSQ total score)	0.05	0.02	9.91	1	**0.002**	1.05	1.02 - 1.08
Inattention (ADHD-RS subscale)	0.05	0.02	4.02	1	**0.04**	1.05	1.001 - 1.10
Hyperactivity/impulsivity (ADHD-RS subscale)	0.03	0.04	0.69	1	0.41	1.03	0.96 - 1.11

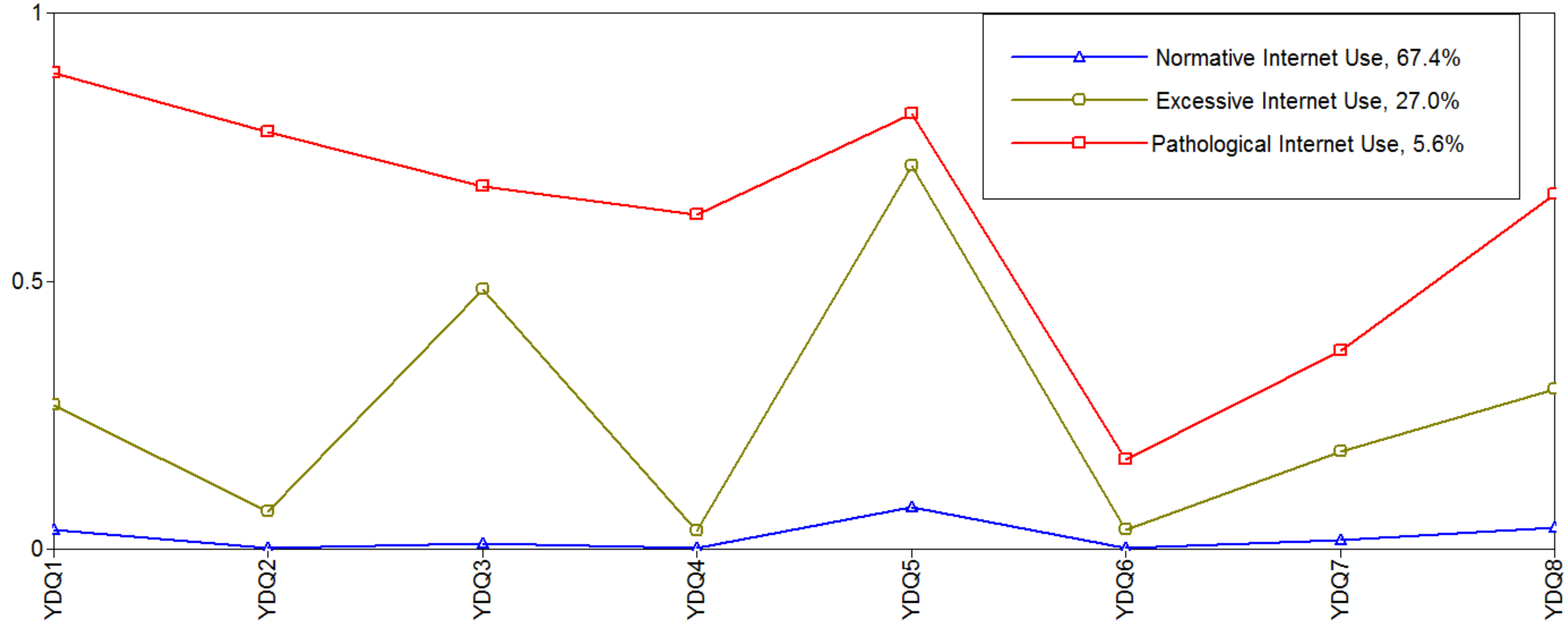
Table 4b. Predictors for the converting patterns of internet addiction (numbers bolded if p < 0.05)

Predictors	β	SE	Wald	df	Sig.	Exp(β)	95% CI
T1 -> T2 (n = 4722)							
Sex	0.17	0.18	0.85	1	0.36	1.18	0.83 - 1.69
School grade							
Grade 5	-0.02	0.24	0.004	1	0.95	0.98	0.61 - 1.59
Grade 6	0.25	0.23	1.19	1	0.28	1.28	0.82 - 2.02
Grade 7	0.36	0.22	2.64	1	0.10	1.43	0.93 - 2.22
ASD traits (ASSQ total score)	0.02	0.02	0.82	1	0.37	1.02	0.98 - 1.05
Inattention (ADHD-RS subscale)	0.06	0.03	5.47	1	**0.02**	1.06	1.01 - 1.12
Hyperactivity/impulsivity (ADHD-RS subscale)	0.01	0.04	0.09	1	0.76	1.01	0.93 - 1.10
T2 -> T3 (n = 4722)							
Sex	-0.23	0.20	1.29	1	0.26	0.79	0.53 - 1.18
School grade							
Grade 5	-0.03	0.28	0.009	1	0.93	0.97	0.57 - 1.68
Grade 6	0.22	0.26	0.73	1	0.39	1.25	0.75 - 2.09

Grade 7	0.45	0.25	3.33	1	0.07	1.57	0.97 - 2.55
ASD traits (ASSQ total score)	-0.004	0.02	0.04	1	0.84	1.00	0.95 - 1.04
Inattention (ADHD-RS subscale)	0.08	0.03	6.66	1	**0.01**	1.08	1.02 - 1.14
Hyperactivity/impulsivity (ADHD-RS subscale)	0.01	0.05	0.09	1	0.77	1.01	0.92 - 1.12
T1 -> T3 (n = 4716)							
Sex	-0.16	0.17	0.90	1	0.34	0.85	0.61 - 1.12
School grade							
Grade 5	-0.14	0.25	0.29	1	0.59	0.87	0.53 - 1.43
Grade 6	0.26	0.24	1.23	1	0.27	1.30	0.82 - 2.06
Grade 7	0.36	0.23	2.48	1	0.12	1.43	0.92 - 2.24
ASD traits (ASSQ total score)	-0.01	0.02	0.31	1	0.58	0.99	0.95 - 1.03
Inattention (ADHD-RS subscale)	0.07	0.02	7.25	1	**0.007**	1.07	1.02 - 1.12
Hyperactivity/impulsivity (ADHD-RS subscale)	0.02	0.04	0.14	1	0.71	1.02	0.94 - 1.10

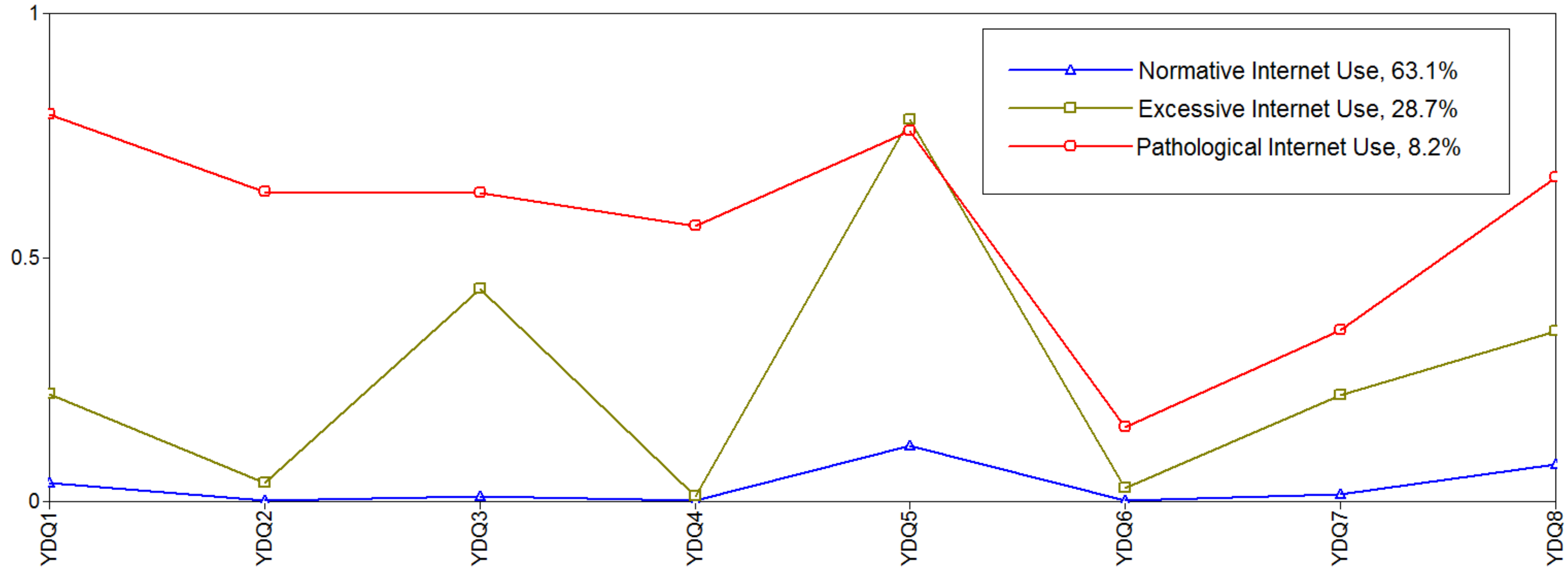
Figure 1: Estimated mean plots for the three-class Latent Class Analysis (LCA) in the year 2016 (Time 1: T1), the year 2017 (T2), and the year 2018 (T3).

Year 2016 (T1)



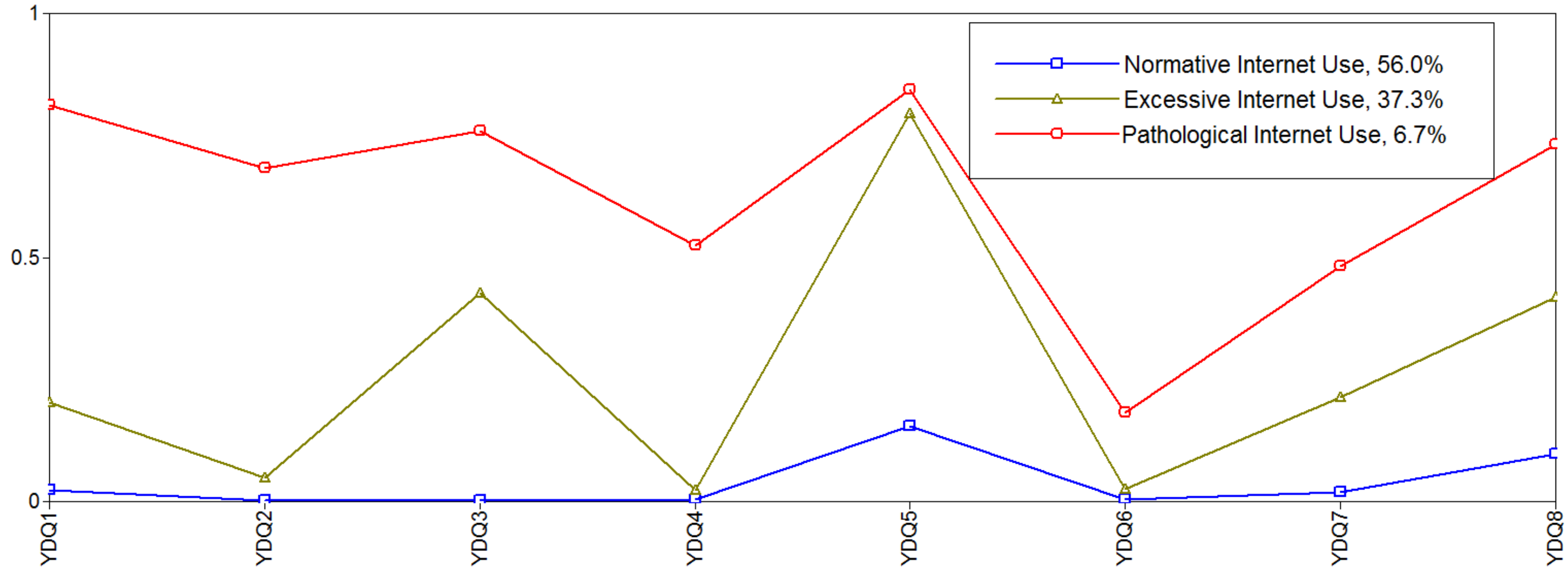
YDQ1: preoccupation, YDQ2: tolerance, YDQ3: repeated failure to control Internet use, YDQ4: withdrawal symptoms, YDQ5: Access internet longer than originally intended, YDQ6: impaired social, academic, or work functioning, YDQ7: lies to others to conceal the extent of Internet use, YDQ8: use of Internet to escape from problems or relieve a dysphoric mood

Year 2017 (T2)



YDQ1: preoccupation, YDQ2: tolerance, YDQ3: repeated failure to control Internet use, YDQ4: withdrawal symptoms, YDQ5: Access internet longer than originally intended, YDQ6: impaired social, academic, or work functioning, YDQ7: lies to others to conceal the extent of Internet use, YDQ8: use of Internet to escape from problems or relieve a dysphoric mood

Year 2018 (T3)



YDQ1: preoccupation, YDQ2: tolerance, YDQ3: repeated failure to control Internet use, YDQ4: withdrawal symptoms, YDQ5: Access internet longer than originally intended, YDQ6: impaired social, academic, or work functioning, YDQ7: lies to others to conceal the extent of Internet use, YDQ8: use of Internet to escape from problems or relieve a dysphoric mood

Supplementary Data 1: testing measurement invariance and examining second-order effect in latent class analysis

We explored measurement invariance constraints prior to including the latent regression paths of an LTA model. We assessed for significant differences in model fit using the likelihood-ratio test (LRT) between a model assuming full measurement noninvariance and that assuming full measurement invariance, where all parameters are constrained to be equal across time. The model assuming full measurement invariance showed a better fit (chi-square distribution with degree of freedom = (109, 24), $p < 0.001$). Thus, we selected the unconditional full measurement invariance model for the LTAs. A second-order effect, which was the lasting effect of internet use status was also examined. In the present study, a second-order effect refers to the effect of status at T1 on status at T3. A first-order effect refers to the effect of status at T1 on status at T2 or the effect of status at T2 on status at T3. Further examinations via the LRT revealed that the second-order effect, in comparison to the first-order effect, significantly improved model fit, indicating the lasting and direct effect of class membership at T1 on class membership at T3.

Supplementary Data 2: The number of students who agreed to participate in the study and who were included in data analyses at each study year

Study year	2016	2017	2018
Total N of students	5537	5457	5304
N of students who agreed to participate in the study	5483	5378	5122
N of students with missing data	54	42	27
N of students included in analyses	5429	5336	5095

Supplementary Data 3: Specification of the final LTA model

Fit indices for T1 supported a three-class solution as the optimal LCA model (lowest BIC and p-value of VLMR-LRT < 0.001). For the T2 and T3 solutions, there was support for both three-class and four-class solutions (**Table 2** in the manuscript). Although the value of the BIC was smaller in the four-class solution at these times points, we selected the three-class solution as the optimal model for T2 and T3 given recommendations for consistency in LTA measurement models [1]. Additionally, careful examination of the four-class solution revealed that two of the four classes in the four-class model were both characterized by a few problems related to internet use that were not considered conceptually distinctive, supporting the three-class solution (PIU, EIU, and NIU) at these time points.

Reference:

Lanza ST, Flaherty BP, Collins LM. Latent class and latent transition analysis. In: Handbook of psychology: Research methods in psychology, Vol 2. Hoboken, NJ, US: John Wiley & Sons Inc; 2003. p. 663–85.