The development of compulsive internet use and mental health: A four year study of adolescence

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Abstract

Is Compulsive Internet Use (CIU) an antecedent to poor mental health, a consequence, or both? Study 1 utilized a longitudinal design to track the development of CIU and mental health in Grade 8 (*N* =1030 males, 1038 females, M_{age} = 13.7), 9, 10, and 11. Study 2 extended Study 1 by examining the kinds of internet behaviours most strongly associated with CIU within males and females. Structural equation modelling revealed that CIU predicted the development of poor mental health, whereas poor mental health did not predict CIU development. Latent Growth analyses showed that both females and males increased in CIU and mental health problems across the high school years. Females had higher CIU and worse mental health than males, and tended to engage in more social forms of internet use**.** We discuss future directions for CIU intervention research.

Keywords: Internet addiction, Compulsive Internet Use, adolescence, mental health

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"The Internet is the first thing that humanity has built that humanity doesn't understand, the largest experiment in anarchy that we have ever had."

— Eric Schmidt, Chief Executive of Google

The internet "experiment" is being conducted with our youth. Rates of internet use are rapidly rising worldwide (Byun et al., 2009; Czincz & Hechanova, 2009), particularly among adolescents (Valkenburg & Peter, 2009; van den Eijnden, Spijkerman, Vermulst, van Rooij, & Engels, 2010b). Existing research indicates that the internet can bring benefits to young people, such as enhanced social connectedness and wellbeing when used to maintain existing friendships (Bessière, Kiesler, Kraut, & Boneva, 2008; Valkenburg & Peter, 2007). Nonetheless, research also suggests a dark side to internet use, in particular when usage becomes excessive and associated with negative consequences in daily life, such as depression (Meerkerk, van den Eijnden, Vermulst, & Garretsen, 2009a; van den Eijnden, Meerkerk, Vermulst, Spijkerman, & Engels, 2008; Young, 1998).

Despite a proliferation of research investigating various aspects of internet use (Byun et al., 2009), we know little about the link between the development of problematic internet usage and other mental health problems (Carli et al., 2013; Ko, Yen, Yen, Chen, & Chen, 2012). Does problematic internet usage lead to mental health problems (the "antecedent" hypothesis), or do mental health problems lead young people to use the internet in problematic ways (the "consequence" hypothesis)? Or does mental health and problematic internet usage mutually influence each other (the "reciprocal" hypothesis)? We sought to address these questions in a 4-year, multi-wave design. Our longitudinal design has the advantage of being able to gather two types of evidence for causality, the extent that variables relate (correlation) and the extent that a purported causal variable precedes a purported effect in time (Ciarrochi, Parker, Kashdan, et al., in Press) . However, as with all real-world longitudinal studies, this study cannot rule out the possible presence of third-variable explanations for the effects (Morgan & Winship, 2007). For example, it is always possible that genetic or environmental factors not measured here can explain the link between problematic internet usage and mental health.

Various terms have been used to describe problematic internet use, including internet addiction disorder, problematic internet use, pathological internet use, and compulsive internet use (CIU) (Meerkerk, van Den Eijnden, Vermulst, & Garretsen, 2009b; Shapira et al., 2003; Windyanto & Griffiths, 2006). Problematic internet use can be broadly understood as an inability to exert control over one's use of the internet, with subsequent negative consequences in valued daily activities (Spada, 2014). The use of the term " internet addiction" is controversial (Spada, 2014), with some researchers arguing that people are addicted to particular activities online, as opposed to the internet per se (Meerkerk et al., 2009b). Nonetheless, conceptually internet addiction appears to share similarities with other addictive disorders, such as withdrawal phenomena, tolerance and negative social repercussions (Pies, 2009). For consistency and in keeping with the Compulsive Internet Use Scale utilised in this study (CIU) (Meerkerk et al., 2009b), we use the term CIU in this paper, recognising the ongoing debate regarding appropriate classification of this disorder (Pies, 2009; Winkler, Dörsing, Rief, Shen, & Glombiewski, 2013).

Longitudinal relationships between CIU and mental health

Numerous studies have shown that various indices of compulsive internet usage tend to show moderate relationships (e.g., r = .20 to .50) with a wide range of indices of mental health and well-being, such as low self-esteem, loneliness, depression, anxiety, and social phobia (Bener & Bhugra, 2013; Bozhurt, Coaskun, Ayaydin, Ibrahim, & Zoroglu, 2013; Cheung & Wong, 2011; Gamez, 2014; Ha et al., 2007; Jang, Hwang, & Y, 2008; Lam & Peng, 2010; Liberatore, Rosario, Martí, & Martínez, 2011; Wang et al., 2013; Yen et al., 2008; Yen, Ko, Yen, Wu, & Yang, 2007). CIU has also been linked to self-injurious behaviour among youth (Lam, Peng, Mai, & Jing, 2009a) and suicidal ideation (Kim et al., 2006; Park, Hong, Park, Ha, & Koo, 2012). Bèlanger and colleagues (2011) examined the U-shaped relationship between internet use and depression among a large sample of adolescents from a representative 2002 Swiss survey. They found that high internet use, as well as non-internet use over the previous month, was associated with higher depression. However research examining the temporal ordering between CIU and mental health outcomes across time is limited (Odlaug & Grant, 2012).

Carli et al., (2013) carried out a systematic review of studies on CIU and psychopathology, including depression, anxiety, ADHD, OCD, social phobia, as well as hostility and aggression. Of the 20 reviewed studies, all but one was cross-sectional, and half targeted adolescent groups (Ko, Yen, Chen, Yeh, & Yen, 2009). The strongest correlations were observed between CIU and depression. More specifically, the effect sizes included four large, five moderate, and five small effects. The majority of included studies reported that CIU was higher among males. In closing, the authors stressed the need for longitudinal research (Carli et al., 2013). Ko et al., (2012) similarly undertook a review examining the association between CIU and psychiatric disorder, identifying 18 studies that fit their criteria. Consistent with the aforementioned review, the vast majority of studies were focused on youth and were predominately undertaken in Asia. Whilst CIU was found to be associated with a range of psychiatric disorders, temporal relationships were inadequately investigated.

Researchers have argued that there is pressing need for longitudinal studies in order to better understand the exact nature of the relationship between CIU and mental health outcomes (Carli et al., 2013; Durkee et al., 2012; Ko et al., 2012; Spada, 2014). It is possible that depressive symptoms may lead to an increase in problematic internet use (Ceyhan & Ceyhan, 2008; Cho, Sung, Shin, Lim, & Shin, 2013; Young & Rogers, 1998), for example perhaps as an avoidance strategy to escape painful thoughts and feelings (Ko et al., 2012; Pies, 2009). Davis (2001) proposed a model of problematic internet use whereby psychopathology was identified as a distal cause, followed by more proximal maladaptive cognitions which were sufficient to cause CIU. Equally, it is reasonable to postulate that excessive internet use may result in poorer mental health outcomes, as proposed by other authors (Carli et al., 2013; Lam & Peng, 2010). For example, increased time spent on the internet may lead to reduced investment in face-to-face relationships with significant others and impairment in meaningful daily activities, and overall reductions in wellbeing (Kraut et al., 1998; Lin & Tsai, 2002; van den Eijnden, Meerkerk, Vermulst, Spijkerman, & Engels, 2008). Of course, relationships between CIU and mental health outcomes may be reciprocally related. Nonetheless the need to better understand the temporal nature of such relationships among youth is clearly warranted as each possibility carries with it differing practical implications for treatment.

Consistent with the observations of previous authors (Carli et al., 2013; Ko et al., 2012), we identified a limited number of longitudinal studies focused on examining the relationships between CIU and mental health outcomes among adolescents (Cho et al., 2013; Gamez, 2014; Ko et al., 2009; Ko, Yen, Yen, Lin, & Yang, 2007; Thorsteinsson & Davey, 2014; van Den Eijnden, Spijkerman, Vermulst, van Rooij, & Engels, 2010; van den Eijnden et al., 2008), including one prospective cohort study (Lam and Peng, 2010).

Gamez (2014) found some evidence that CIU and mental health mutually influence each other. They measured the extent that the internet caused problems in the young person's life (aged 13-17), a variable termed "negative outcomes" that could possibly link to CIU. They found that negative outcomes predicted the development of depression, and depression, in turn, predicted the development of negative outcomes.

Cho and colleagues (2013) found evidence that CIU is a consequence of mental health problems in adolescence, showing that social withdrawal, anxiety and depression during childhood predicted later development of internet addiction. Similarly, Ko and colleages (2009) found that hostility and ADHD were the most significant risk factors for the development of internet addiction for both male and female adolescents. Depression and social phobia predicted later internet addiction among female, but not male participants. In another study, Ko et al (2007) found that low self-esteem predicted the emergence of young adolescents' internet addiction.

There is also evidence that CIU is an antecedent to mental health problems. Lam & Peng (2010) found that young people who were initially free of mental health concerns but demonstrated CIU at baseline were 2.5 times more likely to develop depression at the 9-month follow-up, after adjusting for potential confounding factors. In another study, Van den Eijnden and colleagues (2008) found that instant messenger and use of chat rooms at Time 1 were positively related to CIU at Time 2. In addition, instant messaging was positively related to depression 6 months later; however a reciprocal relationship between depression and instant messaging was not supported. Finally, Gentile and colleagues (2011) conducted a 2-year longitudinal study in children (grades 3) and adolescents (grades 8) and found that increases in pathological gaming predicted future levels of poor mental health in the form of social phobia, anxiety and depression. However, baseline mental health was not controlled for, so it is uncertain whether increase in pathological gaming was an antecedent to poor mental health, or whether increases in pathological gaming and poor mental health merely co-occurred.

Of the longitudinal studies identified, all focused on a relatively limited time period and/or number of time waves. Further, three were restricted to examining one way directional relationships, and could thus not test reciprocal influence models. There is a clear need to build on this earlier research by examining longer time periods that extend across adolescent development, larger samples, and more repeated measures of both CIU and mental health difficulties in order to allow the testing of reciprocal influence models.

Gender differences and stability of CIU

Prevalence rates are complex to estimate from the current literature, given the study samples and measures of CIU differ from paper to paper. According to data from King and colleagues (2012), adult prevalence rates range from .7 to 8.5% in U.S. adult samples, and go as high as 11.9% in a German sample. Student samples similar to the age used in the present study ranged from 1.6% (aged 15-16, South Korea) to 9% (aged 12-18, Singapore). CIU in Australian samples have been estimated to be 5% (aged 15-54) to 8% (aged 14-40). Research generally indicates that CIU is more prevalent among males than females in both Eastern (Bener & Bhugra, 2013; Cao & Su, 2007; Ha et al., 2007; Lam, Peng, Mai,

& Jing, 2009b) and Western countries (Johansson & Götestam, 2004; Morrison & Gore, 2010; Siomos, Dafouli, Braimioties, Mouzas, & Angelopoulos, 2008; Villella et al., 2011).

Research consistently suggests that CIU is moderately stable over time. Huang (2010a) focused specifically on stability of CIU and change across 5 waves obtained at approximately 6-month intervals and found that CIU stability varied between .62 to .75 at 6-month intervals, and was as low as .51 at the longest 2.5 year time interval. Vink , Beijsterveldt, Huppertz et al. (2015) found the test-retest reliability for CIU to be .55 at a 1.6 year interval, and Van Den EIjnden, et al. (2010) found it to be .64 at a 6-month internal. Shek and Yu (2013) undertook a study on Hong Kong adolescents and found that differences in students' mean scores from Wave 1 to Wave 2 were not significant over a 1-year period.

In this paper, we examined the relation between CIU and mental health in two studies. Study 1 sought to examine CIU and mental health across four lags and four years in a large adolescent sample to test three hypothesized models. The **antecedent mode**l assumed that poor mental health is the cause of future CIU. Young people who have mental health issues may use unhelpful coping strategies, such as compulsively using the internet to avoid dealing with their present situation. In contrast, the **consequence model** suggests that CIU takes young people away from genuine social relationships and positive aspects of the physical environment (e.g., exercise, nature). Thus, CIU is expected to lead to diminishing mental health. Finally, the **reciprocal influence model** suggests that CIU is both an antecedent to and a consequence of mental health problems.

Study 2 extended Study 1 by examining the kinds of internet behaviours that are most strongly associated with internet addiction within each gender. Given past evidence of gender differences (Duggan, 2013), we hypothesized that female CIU would tend to involve a social form of internet use (e.g., email, Facebook), whilst males would be more drawn to less social internet activities (e.g., playing games, visiting adult sites, downloading). Study 2 employed the Grade 11 sample of Study 1 and a new Grade 10 sample to ensure a broader age range.

Study 1

Participants

Participants were students from 17 Catholic secondary schools from the East Coast of Australia (Queensland and New South Wales). Catholic schools account for almost one fourth of all secondary school students in Australia and the demographic makeup of this sample broadly reflects that of the Australian population in terms of ethnicity, employment, and religious belief (Australian Bureau of Statistics [ABS], 2010). The Australian government provides a school socioeconomic index in which the average across Australia is 1,000 (http://www.bit.ly/1mJK7KC). The schools in this sample had a similar average score of 1,026 (SD = 43). The students in the sample professed diverse religious views with 18% identifying as atheist, 43% as agnostic, and 39% holding theistic beliefs (though 46% identified as Catholic). The data are made publically available at the following link: figshare.com/s/d7fa92ee4b7411e5af4a06ec4bbcf141

The vast majority of the sample self-identified as Western European/Caucasian with a number of other reported ethnicities, including 2% Indigenous Australian and 3% Asian. Participants reported on their parents' occupation using the coding system based on the ABS (http://www.abs.gov.au/ausstats/abs@.nsf/mf/1220.0). Of the participants, 25% reported their mothers holding professional, technical or managerial positions; 19% reported sales/clerical occupations; 10% each reported homemaker, pensioner or community service; and the remaining participants with smaller proportions reported their mothers working in trades, production, labour, or transport positions. For fathers, 25% reported professional, technical or managerial positions; 34% reported trades, production, labour or transport positions; and remaining participants with smaller numbers in sales/clerical, community service, and pensioner/homemaker.

Informed consent was retained prior to commencement of the study. Participation was voluntary and without financial incentive. Participant data were recorded at four time points. There were 2068 students in Grade 8 (1030 males, 1038 females; M_{age} = 13.7, SD = .45), 2081 (1058 males, 1023 females) in Grade 9, 2023 (1021 males, 1002 females) in Grade 10, and 1735 (832 males, 903 females) in Grade

11. Student numbers in Australia drop during the later years as some students choose to leave high-school and/or pursue vocational training.

Measures

Demographics. In addition to gender, we assessed a number of demographic variables, including mother's and father's employment status, religious belief, and ethnicity.

Compulsive internet usage (Meerkerk, VAn Den Eijnden, Vermulst, & Garretsen, 2009a). The compulsive internet usage scale (CIU) contains items rated on a 5-point scale, ranging from 0 (never) to 4 (very often). Due to space limitations, we used the 10 items that loaded the highest on this 14-item scale, unifactorial scale. Items 11 to 14 were excluded (see Meerkerk, et al, 2009). Example items include "Do you find it difficult to stop using the Internet when you are online?", "Have you unsuccessfully tried to spend less time on the internet?", "Do others (e.g., parents, brothers or sisters, friends) say you should use the internet less?", "Are you short of sleep because of the internet?", and "Do you feel restless, frustrated, or irritated when you cannot use the internet?" The measure was designed to reflect the symptoms of other forms of addiction found in the DSM, including withdrawal symptoms, loss of control, preoccupation, conflict with other activities, and use of addictive activity to escape emotions. In prior research, the measure has shown good, single factor structure and stability across time and different samples, and related in expected directions to criterion variables such as a measure of pathological internet use and time spent on internet. The scale was highly reliable in the present sample (α_8 = .88; α_9 = .89; α_{10} = .89; α_{11} = .90).

Mental health was measured using the 12-item General Health Questionnaire (GHQ-12, Goldberg et al., 1997), utilising a 5-point scale (1 = "Almost never" to 5 = "Almost always") (α_8 = .89; α_9 = .90; α_{10} = .90; α_{11} = .91). People rate the extent to which, over the past few weeks, they have experiences such as, "Lost much sleep over worry?", "Been feeling unhappy and depressed?", and "Felt that you are playing a useful part in things?" The GHQ was originally designed as a screening instrument to identify mental health problems, and has been widely used and validated, and described as "quite possibly the best instrument of its kind (p. 3; (Goodchild & Duncan-Jones, 1985). The GHQ-12 has been shown to be reliable and valid in adolescent samples (Huskees, Ciarrochi, Parker, & Heaven, in press; Tait, French, & Hulse, 2003). In the present sample, the GHQ-12 was reliable in every year (α_8 = .89; α_9 = .90; α_{10} = .90; α_{11} = .91). The scale was scored such that higher scores indicated worse mental health.

Analyses

We utilized complimentary approaches to the analysis of longitudinal data. First, we used autoregressive cross-lag (ACL) models to provide evidence of how CIU and mental health can be used to predict the degree and direction of change in each other. Second, we utilized latent growth curve models (LGC) to explore the relationship between growth trajectories in CIU and poor mental health.

Given that this was a longitudinal study, missing data is a potential concern. It is now well recognized in the social sciences that traditional approaches to missing data (e.g., listwise or pairwise deletion) are inappropriate and can lead to biased parameter estimates. Modern methods like full-information-maximum-likelihood (FIML) provide a principled approach to missing data which uses all the available information for parameter estimation (Enders, 2010). This procedure was employed for all models.

We compared those who completed all waves (completers) with those who only completed some waves (noncompleters). The noncompleters were more addicted to internet in grade 8 (m_c = 1.32 , *SE* = 0.03, m_{nc} = 1.42 , SE = 0.03) and 9 (m_c = 1.42, *SE* =0.03 , m_{nc} = 1.51 , SE = 0.03) and had worse mental health in grade 8 (m_c =1.81 , *SE* =0.02 , m_{nc} = 1.91, SE = 0.02), grade 9 (m_c =1.90 , *SE* =0.02, m_{nc} =2.02 , SE = 0.02), and 10 (m_c = 1.95, *SE* =0.02 , m_{nc} =2.01 , SE = 0.02), but the effects were very small (eta squared between .012 to .002).

Autoregressive cross-lag analyses. ACL models are common methods used to consider temporal ordering of constructs in order to distinguish between alternative causal hypotheses, or directionality of the associations between constructs (i.e., a predicts changes in b; b predicts changes in a; or a and b are reciprocally related). This model's focus is on the relations between one construct at a time point T on change in another construct observed to occur between time point T and T+1.

We used Mplus 7.2 (Muthen & Muthen, Los Angeles, CA) to estimate a series of structural equation models representing the relations between adolescents' CIU and mental health across the four years of the study. All analyses were conducted with latent variables, which enabled measurement error to be estimated and controlled for (Weston & Gore, 2006).

In addition, both a positive and negative method factor was estimated for mental health and CIU, in order to control for response bias due to positively and negatively worded items. The GHQ has long been known to have a somewhat complex measurement structure (Campbell, Walker, & Farrell, 2003). However, while multi-factor items tend to fit the data better, they typically add nothing of substance over a general factor (Shelvin & Adamson, 2005). Much of the misfit in self-report measures such as the GHQ and CIU can be attributed to negative item wording bias (Marsh et al., 2013). One way to deal with this issue is to model the negatively and positively worded items as separate factors but also model a global factor including both components (Marshall, et al, in press).

Robust maximum likelihood estimation was used such that standard errors and a chi-square test statistic were robust to non-normality. The data for this study had a nested structure with students nested within the 17 schools. To control for the nested structure, we used a sandwich estimator in Mplus via the TYPE=COMPLEX command. Models were considered to fit the data well if (a) the solution was well defined, (b) parameter estimates were consistent with the theory proposed, and (c) the fit indices were acceptable, giving emphasis to fit indices which are appropriate for larger sample sizes (McDonald & Marsh, 1990). Specifically, we provide three additional fit indices in addition to chi-square. The Tucker–Lewis index (TLI) and comparative fix index (CFI) $\geq .90$, and the root mean square error of approximation (RMSEA) $< .08$ were considered to provide evidence of model fit in accordance with commonly accepted criteria (Bentler & Bonett, 1980; Browne & Cudeck, 1993).

Tests of invariance commenced with the least restrictive configural model where all model parameters are freely estimated across time (Model 1). If the hypothesis of configural invariance is not rejected, stronger forms of measurement invariance can be utilized. In the second model, termed "loading invariance," factor loadings of each indicator were constrained to be equal across time. If this hypothesis is retained, it means that the constructs have the same meaning at each time point. Loading invariance is an assumption of covariance-based models such as cross-lagged models preformed here (Nagengast et al., 2011).

In the third model, termed "intercept invariance," both the factor loadings and the intercepts were held to be constant across groups. Full intercept invariance indicates that mean level changes in the indicators are adequately captured by changes in the underlying means of the latent construct (Little, Preacher, Selig, & Card, 2007). If this hypothesis is rejected, then partial invariance model can be tested. The goal is to free intercepts in sets such that the modification indices suggest freeing one set would be positive and the other set would be negative (Asparouhov & Muthen, 2014).

An increasingly frequent approach when multiple waves are present is to test whether the interrelationships between constructs in an ACL model have reached a developmental equilibrium – i.e., whether the effect of one variable on another is consistent across time lags. We sought to test this model in the present data.

Evidence of invariance comes from comparing a well-fitting baseline model to alternate nested models. Invariance sensitivity to sample size of the chi-square that underlies the widespread use of fit indices (e.g., RMSEA, CFI, and TLI) does not merely relate to model fit but additionally log-likelihood ratio tests that are often used to conduct such model comparisons. Therefore, in this study we used the criteria by Cheung and Rensvold (2002) who suggest invariance between nested models if CFI is ≤ .01 (we utilized the same criteria for the TLI), and the criteria described by Chen (2007), who suggests invariance between nested models if RMSEA is ≤ .015.

Latent growth curve modelling. ACL models focus on temporal ordering and generally give limited indication of individual growth over time. Conversely, LGC models provide considerable flexibility in estimating growth trajectories, including linear, various polynomial, and other complex growth patterns (Diallo, Morin, & Parker, in press; Ram & Grimm, 2007). LGC modelling decomposes variance in the repeated measures of a construct into intercept and slope components respectively, reflecting the initial level and growth in the estimated developmental trajectories (Duncan, Duncan, & Strycker, 2006). LGC allows one to test the significance of the growth component (mean) and of the presence of inter-individual variability on this growth component (variance). Additionally, comparisons of nested models can be used to compare trajectories, allowing for a test of whether mental health and CIU show a linear or non-linear trajectory.

Preliminary analyses

We first examined demographics, checking for variables that may relate to both internet addiction and mental health and therefore could act as a potential confounds. We required a value to be significant at $p < .005$, which reduced the problem of Type 1 error, given the large number of tests (e.g., one for each year of CIU and mental health). There were no significant links between internet addiction, mental health, and occupation of fathers and mothers, religious identification, or ethnicity. There was also no link between marital status and CIU, but there was a significant link between marital status and mental health in Grade 8 and 9, $Fs > 5$, $ps < .001$. Young people tended to have better mental health if their parents were married ($m_8 = 1.82$; $m_9 = 1.92$) compared to if their parents were separated ($m_8 = 1.95$; $m_9 = 2.10$) or divorced ($m_8 = 1.98$; $m_9 = 2.04$). However, there were no significant links between marital status of parents and participants' internet addiction.

Finally, we calculated correlations between internet addiction and mental health, as presented in Table 1. There were small to moderate correlations between CIU and mental health. Both CIU and mental health also showed moderate levels of stability, with about 6 to 25% of variance of a variable being explained by an earlier measure of the variable. The degree of stability decreased with increasing space between years.

Autoregressive cross-lag results

We used ACL to first establish the most parsimonious, well-fitting model (see above discussion), and then to examine the extent that CIU was an antecedent, consequence, or reciprocally related to mental health. All models controlled for gender, which are discussed in more detail in the next section. Table 2 presents the results of the structural equation models. The configural model adequately fit the data (M1), and the loading invariant model (M2) did not produce a substantial change in fit. The full intercept invariance model (M3a) did not result in substantial drop in RMSEA or TLI, but the change in CFI from model 1 was .012, which violated our criteria for invariance. Examination of the intercept modification indices indicated that the item, “Are you short of sleep because of the Internet?” produced the largest modification indices, and steepest positive expected parameter change. This indicates that being short of sleep grew at a different rate than the other items; in this case at a faster rate. In contrast, the item, “Do others (e.g., parents, brothers or sisters, friends) say you should use the Internet less?” had modification indices between 18 and 85 and showed the steepest negative expected parameter change. This indicates that others discouraging internet use grew more slowly than the other items. Freeing this pair of parameters substantially improved fit of the model (M3b) and did not result in a substantial difference in fit from Model 1. All subsequent models included partial intercept invariance. As presented in the Supplementary Materials, the full intercept and partial intercept produce nearly identical results in all analyses.

As can be seen in Table 2, assuming single year effects (M4) or developmental equilibrium (M5) had very little effect on the fit indices. Thus, the partial intercept invariant, developmental equilibrium model was considered best.

The results of the final model are presented in Figure 1 below. CIU showed substantial stability across the years, whereas the stability of mental health was more modest. The cross-lags clearly support the antecedent model, and are inconsistent with the consequence or reciprocal influence model. CIU appears to be a precursor to the development of poor mental health, but poor mental health does not predict the development of CIU. We also ran the final model within each gender to assess the reliability of effects. Consistent with Figure 1, CIU was a reliable predictor of mental health with both males (β = .09, p < .001) and females (β = .08, p < .001), whereas mental health did not predict internet addiction (βs < .022, p > .25).

Latent Growth Curve analyses

The latent growth curve analyses (LGC) explored growth in the trajectory of both CIU and mental health, within gender, and over the four time periods. The core model is described above. Due to the complexity of the measurement structure (latent variables and corrections for positive and negatively worded items bias), direct estimation of the growth curves was not possible. To overcome this, we utilized MPLUS to generate five plausible value data sets from Model 3b above, and these five data sets where then used in multiple imputation LGC analyses. Plausible values are used to represent latent constructs in a number of fields including achievement scores in PISA and TIMSS (Asparouhov & Muthen, 2010). As opposed to factor scores, the use of plausible values account for the uncertainty that comes from estimating an individual's score on a given latent variable, thus retaining the benefits of latent variable modelling but in a way that allows for the estimation of complex LGC models from data with complex measurement model properties.

We compared the fit of a model with linear growth ($\chi^2(26) = 131.03$) to one with both linear and quadratic growth ($\chi^2(11) = 52.85$), and found that estimating quadratic growth significantly improve the fit of the model (ΔCFI = .32), and produced a well-fitting model, CFI = .98, TLI = .93, RMSEA = .037.

The latent growth analyses revealed that the mean slope factor was significant for both females (Addiction μ = 0.12, SE = 0.04, p <.005; Mental health μ = 0.11, SE = 0.02, p <.001) and males (Addiction μ = 0.07, SE = 0.03, p <.05; Mental health μ = 0.06, SE = 0.01, p <.001). There was also a significant quadratic component for the development of females mental health (μ = -0.02, SE = 0.004, p <.001), but no other significant quadratic effects. Figure 2 illustrates the pattern. Both CIU and mental health problems increased during the school years, and the increase in poor mental health for females was particularly steep between grades 8 and 9 (the quadratic effect). However, there were no statistically significant gender differences in slope or quadratic effect (p>.1). The only difference involved the mean levels, with females showing both higher CIU and worse mental health than males.

Examination of the correlations between intercept and growth parameters revealed a negative relationship between intercept and slope for both CIU (r= -.34, p< .001) and mental health (r = -.39, p< 05), consistent with a regression to the mean phenomena. There was a highly significant relationship between the mean level of CIU and poor mental health (r=.36, p< .001), and the slopes of these two variables (r=.62, p< .005), indicating that those with high CIU also tended to exhibit worse mental health, and increases in CIU were associated with increases in poor mental health.

Study 2

Study 1 established that CIU acts as an antecedent to poor mental health, but did not identify the specific internet behaviours that were associated with CIU and mental health problems. Huang's (2010b) meta-analysis suggests that higher frequency of internet usages had small detrimental effect on well-being, with effect sizes at about r = -.05. We sought to extend this research in Study 2 by linking internet usages to CIU. Are specific internet activities more linked to CIU than others? Thorsteinsson and Davey's (2014) research suggests that higher internet usage is not always bad. Some aspects of internet usage, such as using instant messaging and social networks, might contribute to lower CIU.

Participants

We measured internet behaviour in the grade 11 sample reported in Study 1 and a new grade 10 sample. The new sample involved the seven Catholic schools that participated in the Queensland component of Study 1 and consisted of 687 participants (350 male, 327 female; 10 unreported).

Measures

Mental health and Compulsive Internet Usage measures were the same as described in Study 1. *The Internet Behaviour Questionnaire* was drawn from the work of Van den Eijnden et al (2008). It asked participants the extent to which they have engaged in a number of internet behaviours over the past six months, ranging from 1 (never) to 5 (a great deal). The scale included seeking information, surfing, gaming, downloading music, films, software and so forth, emailing, chatting in a chat room, instant messaging, Facebook, Twitter, accessing adult only sites, and other.

Results

The key findings relating internet behaviour to gender and CIU are presented in Table 3. As hypothesized, males were more likely than females to engage in gaming and accessing adult sites, whereas females were more likely to engage in email and Twitter. In grade 10, CIU was more strongly associated with gaming for males, and Facebook for females, but these differences disappeared by grade 11. CIU was never associated with seeking information.

Finally, we examined the link between internet behaviour and concurrent mental health issues. There was little link between poor mental health and frequency of internet behaviour in year 11, with only the downloading of music, films, and software being associated with worse mental health, $r = .12$, $p < .001$. There were a few more links in grade 10, with poor mental health associated with frequency of instant messaging ($r = .17$, $p < .001$), Facebook usage ($r = .16$, $p < .001$), and Twitter ($r = .12$, $p < .005$).

Discussion

These two studies sought to examine the nature of internet addiction and its developmental consequences for mental health. Study 1 provided clear support for hypothesis that CIU was an antecedent to the development of poor mental health across the four years of the study. Of particular concern, CIU and poor mental health problems increased from Grade 8 to Grade 11, with increase in one variable associated with increases in the other. Study 2 suggested that, within both males and females, CIU was associated with every form of internet behaviour except seeking information. However, internet addiction behaviour is likely to look different for males and females given they had different baseline patterns of internet activity: females engaged in more emailing and Twitter, whereas males engaged in more gaming and accessing adult only sites. Internet addiction appeared to be an "equal opportunity problem": It was equally likely in families with different occupations, ethnicity, and marital status.

The results should not be interpreted as indicating that higher frequency of internet behaviour is associated, necessarily, with higher CIU. Future research needs to focus on the function of the internet behaviour. For example, we find instant messaging to be associated with higher CIU, but we did not measure the function of the messaging. Thorsteinsson and Davey (2014) show that instant messaging may be associated with lower CIU if it is done in the service of staying in contact with friends.

What comes first: CIU or mental health problems?

Past research has sought to address this question in relatively short-term longitudinal studies that often did not involve the measure of CIU and mental health at both time periods. Lam and Peng (2010) found that CIU predicted later development of psychopathology at a 9-month follow-up. Van den Eijnden et al. (2008) showed that instant messaging was related to depression 6 months later, but the relationship was not reciprocal. Depression did not predict instant messaging. The present study extends this past research by extending the measurement period across most of the high-school years. We found clear evidence that CIU was a consistent antecedent to the development of poor mental health, and this effect was stable across the three time lags.

Past researchers have suggested that avoidant behaviour and mental health problems can form part of a "downward spiral", with more avoidant behaviour leading to worse mental health, and worse mental health, in turn, leading to an increase in avoidant type behaviour (Ciarrochi & Bailey, 2008; Williams, Ciarrochi, & Heaven, 2012). However, our present study found no evidence of this downward spiral: Poor mental health did not predict increases in CIU. The effects appeared to flow in one direction, with CIU leading to worsening mental health.

The effects involving CIU and mental health tended to be in the small to moderate range. CIU predicted about 4% of the variance in mental health at a one year lag, which puts it in the average effect size range according to Hemphill's review (2003). After controlling for baseline mental health, this predictive relationship was reduced to 1%. This is a small effect and similar to other cross-lag effects in the area. For example, the cross-lag link between parenting practices and future compulsive internet usage was .02 to .10 (van den Eijnden et al., 2010), between CIU and future depression was .14, between depression and future CIU was .16 (Gamez, 2014), and between instant message and depression was .10 (Van Den Eijnden, et al. , 2008). Importantly, the link between CIU and worsening mental health was stable across the three time lags, which means that a small effect of CIU over one year could accumulate into a large effect over several years. For example, if a young person is consistently one standard deviation above average in CIU from Grade 8 to 11, they can expect to see their mental health drop by about 1/3 of a standard deviation during this same time period.

Limitations

We found no mental health "consequences" effects and no moderation by gender, which is somewhat inconsistent with other findings. Ko et al (2007) found that depression and social phobia predicted later internet addiction amongst female, but not males. Van den Eijnden et al. (2008) found that loneliness lead to increases in instant messaging. It is possible that the General Health Questionnaire used in our study is too broad to pick up the consequence of poor mental health. Future research is needed to examine the effects of specific states, such as social phobia and loneliness, on the development of CIU.

One limitation of longitudinal research is that it can never eliminate the possibility that a third variable explained the effect. Cross-lag analyses do eliminate some third variables problems. For example, in the present study we examined the link between CIU and future mental health when controlling for concurrent levels of mental health. This control should reduce the problem of common method variance between the scales, since what is common in the scales is expected to be removed from the estimates (Lindell & Whitney, 2001). However, there still might be other unmeasured variables related to development, environment, or genetics that explain changes in both CIU and mental health. Such variables might include puberty, changes in social relationships, and awareness of sexual orientation. Future longitudinal research needs to measure the most likely third variable explanations for our finding.

Future research is also needed to examine the mediators between CIU and poor mental health. We need a better understanding of why CIU is associated with worsening mental health. Perhaps excessive internet usage reduces investment in face-to-face relationships, or impairs meaningful daily activities (Kraut et al., 1998; Lin & Tsai, 2002; van den Eijnden et al., 2008). Perhaps part of the negative consequences of CIU stems from the disruption in sleep patterns, or in healthy physical activity.

Finally, future studies can advance our understanding of CIU by assessing variables that are likely to influence CIU (antecedents) and explain the link between CIU and mental health (mediators). For example, it will be important to measure parenting practices concerning internet (van den Eijnden et al., 2010). It might also be worth assessing attitudes and internet usage within friendship networks. Recent research suggests that characteristics like hope tend to cluster in groups, and the level of group hope predicts well-being over individual hope (Parker, Ciarrochi, Heaven, et al, 2015). Perhaps some social groups are more likely to promote CIU amongst its members than other groups. Concerning mediators, we would hypothesize that CIU works through at least two mechanisms: Diminishing genuine social connections, a major source of reinforcement, and diminishing opportunities for physical activity. Future research is needed to investigate these hypotheses further.

Implications

Much more research needs to be done to specify the best possible intervention for CIU, but past research provides some hints about what one might do. Parents might be the most natural point to intervene, given that they are able to monitor young people's internet usage perhaps better than other adults. However, the approach that parents should take may not be intuitively obvious to them. Van den Eijnden (2010) found that the parenting practice of applying strict rules regarding time of internet usage was associated with higher, not lower, CIU. In contrast, CIU may be reduced when parents engage in high quality communication in which young people feel comfortable, understood, and taken seriously. It may also be helpful to focus on the content of the internet behaviour, rather than on quantity (van den EIjnden, 2010).

Future research is needed to examine the benefits of such common therapy components as awareness building and value clarification in combating CIU. However, in designing these interventions, it is important to keep in mind how CIU may differ from other addictions. For example, with drug usage, higher frequency of usage is generally considered more problematic. The same may not hold true for internet usage. Higher frequency of usage may be associated with either positive or negative outcomes, depending on the function of that usage. For example, the internet can be used to build social relationships and seek information, or it can be used as a way of obtaining short-term stimulation and reward whilst sacrificing longer term well-being. Further, for many young people complete abstinence from internet activity is impossible due to demands of school. Future research is needed to identify how cognitive behavioural interventions can be tailored to the context of CIU and young people.

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Tables and Figures

Table 1

Correlations between Compulsive Internet Use and Low Mental Health for Grade's 8 to 11.

Measure	1	2	3	4	5	6	7	8
1. CIU 8	--	.54**	.43**	.37**	.18**	.21**	.08*	.13**
2. CIU 9	.64**	--	.56**	.50**	.13**	.26**	.15**	.19**
3. CIU10	.52**	.64**	--	.59**	.18**	.18**	.24**	.22**
4. CIU11	.40**	.53**	.68**	--	.12*	.25**	.16**	.31**
5. MH8	.31**	.27**	.17**	.19**	--	.47**	.31**	.24**
6. MH9	.27**	.27**	.21**	.17**	.49**	--	.41**	.35**
7. MH10	.19**	.20**	.24**	.17**	.41**	.47**	--	39**
8. MH11	.19**	.17**	.22**	.29**	.32**	.40**	.47**	--

Note: CIU= Compulsive internet Use. MH = Low Mental health. Intercorrelations for male participants are presented about the diagonal and for female participants are presented below the diagonal.****p,>001*,** *p*< .01, **p*< .05

Table 2

Measurement invariance and developmental equilibrium models

Model	χ^2	df	RMSEA	CFI	TLI
M1 Configural model	9461.5	3652	.024	.925	.920
M2 Loading invariance	9641.8	3706	.024	.923	.919
M3a Full Intercept invariance	10485.1	3766	.025	.913	.910
M3b Partial intercept invariance	10143.6	3760	.025	.918	.914
M4 Single-year autocorrelation and cross-lag	10210.2	3772	.025	.917	.914
M5 Developmental equilibrium model	10218.3	3780	.025	.917	.914

Note. RMSEA = root mean square of approximation; CFI = comparative fit index; TLI = Tucker-Lewis index. Model 5 was chosen as the best model and the results are presented in Figure 1.

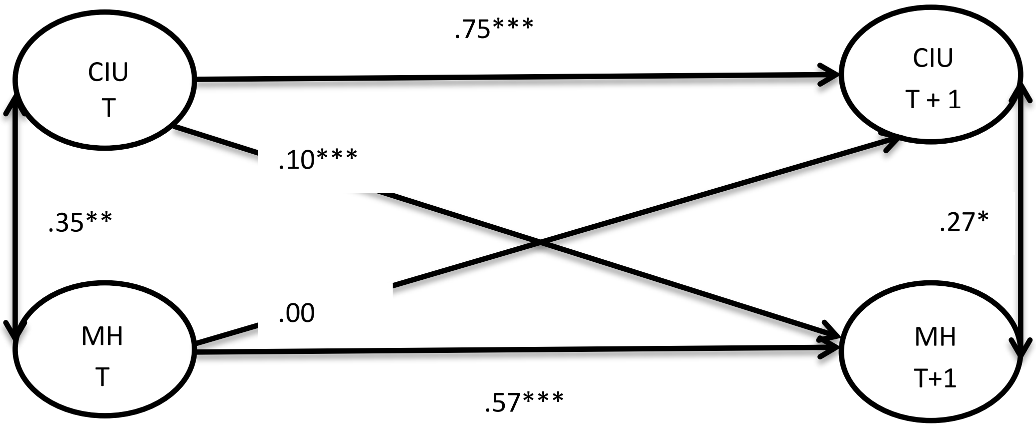
Table 3

Mean frequency of different internet behaviours and their relationship (r) with compulsive internet usage

Internet behaviour	Statistic	Grade 10		Grade 11	
		Males	Females	Males	Females
Seeking information	M	3.81	3.86	3.87	3.96
	SD	1.00	0.98	1.10	1.10
	r	.00	-.01	.01	.00
Surfing	M	3.05	2.88	3.00	3.06
	SD	1.30	1.40	1.40	1.40
	r	.27**	.21**	.16**	.23**
Gaming	M	3.39_a	2.08_a	3.23_a	2.10_a
	SD	1.30	1.10	1.38	1.20
	r	$.39_a$**	$.23_a$**	.23**	.25**
Downloading music, films etc	M	3.64	3.52	3.65	3.69
	SD	1.20	1.30	1.20	1.20
	r	.24**	.31**	$.21_a$**	$.31_a$**
E-mailing	M	2.54_a	2.98_a	2.64_a	3.23_a
	SD	1.20	1.20	1.20	1.20
	r	.16**	.01	.07	.03
Chatting in a chat room	M	2.63	2.45	2.25	2.21
	SD	1.50	1.50	1.40	1.40
	r	.22**	.22**	.14**	.18**
Instant Messaging	M	3.29	3.57	3.28	3.46
	SD	1.50	1.40	1.47	1.50
	r	.29**	.30**	.14**	.26**
Facebook	M	3.83	3.86	3.94	3.97
	SD	1.40	1.50	1.30	1.40
	r	$.26_a$**	$.48_a$**	.13**	.22**
Twitter	M	1.39_a	1.73_a	1.49_a	1.63_a
	SD	0.93	1.30	1.10	1.20
	r	.10	.17**	.12**	.20**
Accessing Adult only sites	M	2.56_a	1.29_a	2.78_a	1.33_a
	SD	1.40	.81	1.40	0.90
	r	.30**	.19**	.19**	.18**

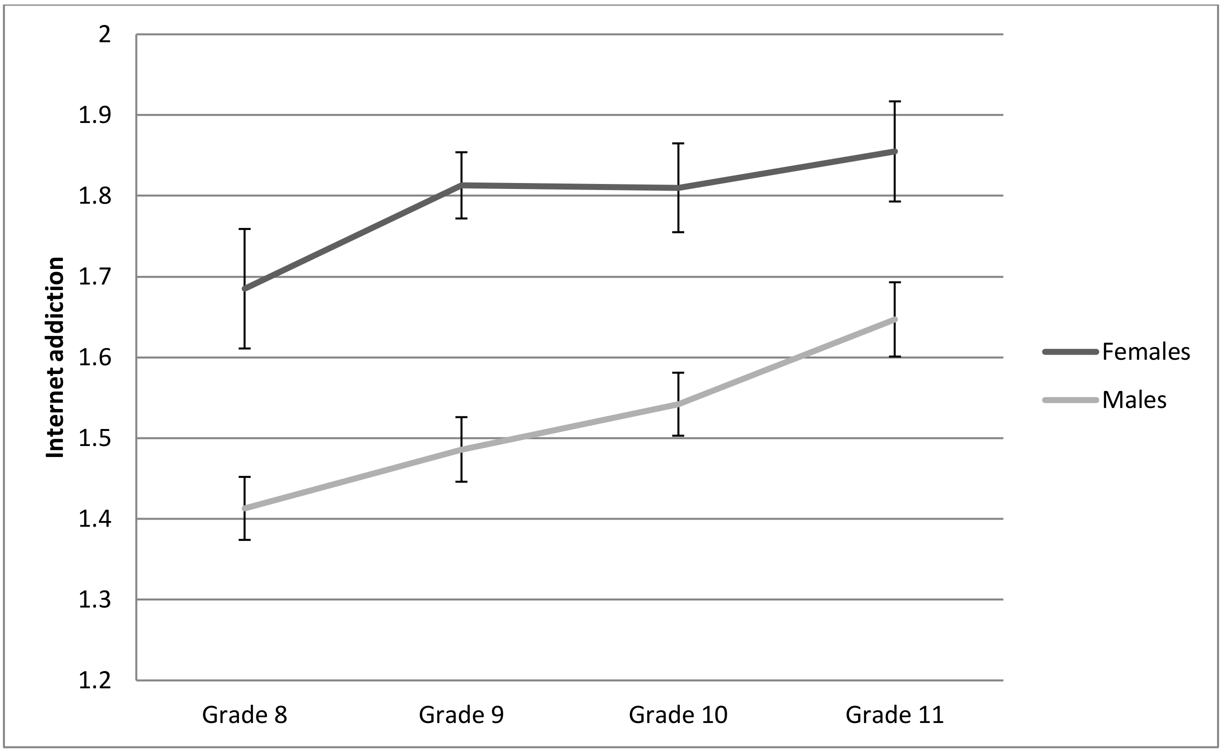
Note. Male and Female means and correlations sharing subscripts within a year are significantly different from each other at p< .01. N for grade 10 was 332 Males and 309 Females. N for Grade 11 was 806 Males and 882 Females.

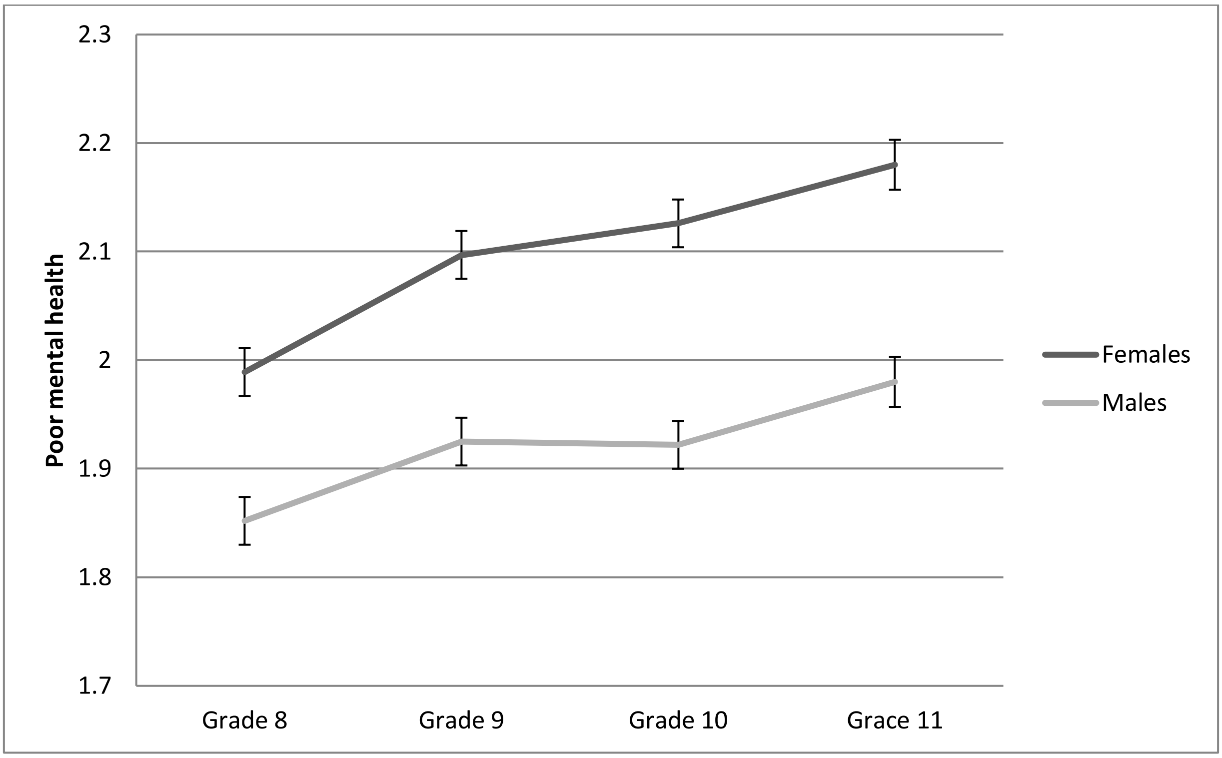
Figure 1: Developmental equilibrium model: Autocorrelation and cross-lagged effects (Betas) for compulsive internet use (CIU) and poor mental health (MH) (Time T) predicting across a year (Time T +1), averaged across four waves of data.



Note. This is Model 5 from Table 2. *p< .05, ** p< .01; ***p < .001.

Figure 2: Latent means and standard error bars of CIU and mental health across gender and school grade





Supplementary materials

Intercept invariance and partial invariance

Table 1. Autoregressive and cross-lagged effects of internet addiction (Int. Add.) and Mental ill-health (model 4) across one-year lags

Autoregressive /cross-lagged effects	Beta	SE
T1 Int. Add. → T2 Int. Add.	.71***	.024
T1 Int. Add. → T2 Mental ill-health	.12***	.024
T1 Mental ill-health → T2 Mental ill-health	.59***	.038
T1 Mental ill-health → T2 Int. Add.	.05	.033
T2 Int. Add. → T3 Int. Add.	.75***	.023
T2 Int. Add. → T3 Mental ill-health	.06**	.023
T2 Mental ill-health → T3 Mental ill-health	.59***	.038
T2 Mental ill-health → T3 Int. Add.	-.01	.019
T3 Int. Add. → T4 Int. Add.	.78***	.023
T3 Int. Add. → T4 Mental ill-health	.12***	.042
T3 Mental ill-health → T4 Mental ill-health	.54***	.033
T3 Mental ill-health → T4 Int. Add.	-.03	.033

*p< 05, **p< .01, ***p< .001;

Note: The results were virtually identical regardless of whether we assumed full intercept invariance or partial intercept invariance

Table 2: Latent means (and standard errors) for internet addiction (IA) assuming full and partial interept invariance.

	Males		Females	
Variable	Full invariance	Partial Invariance	Full invariance	Partial invariance
Grade 8 IA	1.40 (.039)	1.41 (.039)	1.67 (.074)	1.69 (.074)
Grade 9 IA	1.49 (.040)	1.49 (.040)	1.82 (.042)	1.81 (.041)
Grade 10 IA	1.55 (.038)	1.54 (.039)	1.82 (.055)	1.81 (.055)
Grade 11 IA	1.65 (.047)	1.65 (.046)	1.86 (.062)	1.86 (.062)