Longitudinal Trajectories, Social and Individual Antecedents, and Outcomes of Problematic Internet Use among Late Adolescents

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Abstract

Given the detrimental effects associated with problematic internet use (PIU) and the need to better understand its nature and evolution, the present study examined the development of PIU in a sample of 1750 adolescents (aged 16-19) from Finland over a three-year period. We documented the social (loneliness, perceived maternal and paternal behaviors) and individual (sex) antecedents, as well as the outcome implications (depressive symptoms, substance use, academic achievement) of PIU trajectories. Outcomes also predicted PIU trajectories. Latent curve modeling revealed an initially moderate, and subsequently decreasing trajectory of PIU. PIU was predicted by loneliness, paternal neglect, maternal care, depressive symptoms, and being male. In turn, PIU trajectories predicted increases in depressive symptoms and substance use, but decreases in academic achievement.

Keywords: problematic internet use (PIU); trajectories; longitudinal; loneliness; depressive symptoms; perceived parenting practices; substance use

Internet use has grown exponentially over the last decade, to the extent that it is now an integral part of everyday life, a core source of leisure and information, in addition to facilitating the establishment and maintenance of social communication. Not surprisingly, the number of Internet users has increased substantially in the last decade, reaching up to four billion users (McDonald, 2018), and these increasing rates of internet use also apply to adolescents (Smahel et al., 2020). Current research literature has established the benefits of Internet use in the form of, for instance, exposure to positive virtual learning experiences (Ito et al., 2020). However, Internet use can be a double-edged sword and research (e.g., Young, 1998) has highlighted the risks associated with excessive internet use, showing that excessive users may come to demonstrate signs of problematic or addictive Internet use (PIU). Among adolescents, prevalence estimates of PIU range between 0.8% and 26.7% (Kuss et al., 2014).

Research seeking to uncover the mechanisms underpinning the emergence of PIU among adolescents is important given that, according to the Differential Susceptibility to Media Effects Model (Valkenburg & Peter, 2013), media use is purported to have its strongest influence both in childhood, and in the late adolescence-early adulthood period. This perspective thus suggests that PIU developed during the late adolescence-early adulthood period is likely to persist into middle adulthood (Hurd et al., 2014). This should not come as a surprise when we consider the fact that this developmental period is the one during which developing individuals will come to develop habits of Internet use that will move beyond personal use to encompass more professional types of utilization. Unfortunately, despite this theoretical importance, little is known about the developmental trajectories of PIU during late adolescence and early adulthood, as well as about its core determinants and consequences. The present study seeks to shed light on these questions by investigating PIU trajectories over three years among a sample of late adolescents followed into early adulthood. More importantly, we examine the role of loneliness, perceived parenting behaviors, and sex as antecedents of these trajectories, and the extent to which these trajectories are related to key outcomes of depressive symptoms, substance use, and academic achievement. We also tested how the outcomes predicted PIU trajectories to test the directionality of their associations.

Problematic Internet Use and Its Longitudinal Development

Various terms and definitions have been used, often interchangeably (e.g., Laconi et al., 2014), to describe PIU, including Internet addiction (Young, 1998), compulsive Internet use (Ciarrochi et al., 2016), or pathological Internet use (Davis, 2001). However, at their core, these various appellations all refer to the same underlying phenomenon (Anderson et al., 2017). Therefore, in line with prior studies (Anderson et al., 2017), the present study conceptualizes PIU as a problematic, excessive and time-consuming engagement with and use of the Internet. Similar to the "generalized Internet addiction" phenomenon proposed by Brand et al. (2014; see also Davis, 2001), PIU covers all forms of internet applications, thus reflecting a multidimensional overuse of the Internet. Whilst acknowledging the ongoing scientific debate surrounding the diagnostic classification of internet addiction (Anderson et al., 2017; Winkler et al., 2013), the present study thus rather considers PIU as general psychological condition varying in terms of severity.

Even though research has already been conducted to help understand the emergence of PIU, no theoretical model has ever been formally proposed to let us anticipate how PIU trajectories will unfold across the late adolescence-early adulthood period. However, from the perspective of personality theory, this period tends to be accompanied by increases in conscientiousness, emotional stability, and agreeableness (Vecchione et al., 2012). These changes are purported to reflect normative growth processes whereby adolescents become more disciplined and self-regulated adults (Caspi et al., 2005; Roberts et al., 2001). However, these changes also suggest that initially leisurely activities might either be discarded or become part of one's ongoing repertoire during this critical developmental period.

Furthermore, the Dualistic Model of Passion (DMP; Vallerand, 2015), which highlights the need to differentiate between harmonious and obsessive levels of passionate involvement in a variety of activities, has already been applied to enrich our understanding of youth involvement in various forms of online activities (e.g., Tóth-Király, Bőthe, Márki, et al., 2019). According to the DMP (e.g., Vallerand, 2015), harmonious passion reflects a high level of involvement in an activity driven by interest and pleasure that has been integrated with other life areas. In contrast, obsessive passion reflects an excessive level of engagement in an activity that is mainly driven by internal or external pressures and contingencies in a way that starts to escape one's volitional control and tends to interfere with other life areas. Although passion for an activity might initially emerge spontaneously, the crystallization of a passion into an obsession typically involves a slow developmental process via which the level of passion initially increases and decreases part of a series of transactions with the environment (Vallerand, 2015), before becoming more chronic. For these various reasons, obsessive passions bear strong conceptual similarities with PIU and other types of addictive behaviors. This similarity suggests that processes similar to those at play in the emergence of an obsessive passion may also be at play in the development of PIU, leading us to expect moderately stable PIU trajectories during this developmental period.

Understanding the development of PIU over the course of the late adolescence-early adulthood period could guide the development of intervention strategies. Observing that PIU tends to follow a stable, and possibly increasing, trajectory consistent with the development of a rigid trait-like psychological state would support the need to devise early intervention strategies seeking to prevent its emergence when youth are still in school. Conversely, identifying less fixed trajectories consistent with a greater level of malleability and environmental reactivity would rather support the use of ongoing intervention strategies.

The proposition that PIU might demonstrate some change in late adolescence has received empirical support. Stability in ratings of PIU has traditionally been examined with analyses of mean-level stability in the form of repeated measures ANOVAs (e.g., Yu & Shek, 2013), of rank-order stability in the form of longitudinal correlations (e.g., Salmela-Aro et al., 2017), or via autoregressive models (e.g., van der Eijnden et al., 2008). Although these studies provide information related to the rank-order (correlations, autoregressions) or mean-level (ANOVAs) stability of PIU, they are unable to inform research regarding the intra-individual trajectories that characterize PIU development among specific adolescents, or about the presence of inter-individual variations in the shape of these trajectories.

The present study addresses these limitations by relying on latent curve modeling (LCM) to more specifically address issues pertaining to intra-individual stability and change in PIU trajectories, and to inter-individual variations in the shape of these trajectories (Bollen & Curran, 2006). To our knowledge, only three studies have relied on similar methodologies to study PIU development. Ciarrochi et al. (2016) reported that PIU generally tended to increase during high school for Australian middle adolescents. Conversely, Shek et al. (2018) reported a slight decrease in PIU over three years among Hong Kong early-to-middle adolescents. Finally, Li et al. (2019) reported decreasing trajectories of PIU over a six-month period among a sample of Chinese middle adolescents, but also revealed the presence of significant inter-individual variability in the shape of these trajectories, which could explain the previously reported discrepant results. Yet, results pertaining to PIU trajectories remain inconclusive, requiring further investigations. This is the objective of the present study.

Antecedents of Problematic Internet Use

In order to be able to devise cost-effective intervention strategies for the reduction of PIU, it is important to obtain a clearer picture of the mechanisms involved in its development. For this purpose, we relied on the Cognitive-Behavioral Model of PIU (Davis, 2001) that identifies social isolation and the lack of social support as key antecedents of PIU. In accordance with this theoretical model, we considered loneliness and perceived parenting behaviors as predictors of PIU trajectories. However, based on tentative evidence suggesting that PIU might differ as a function of sex (e.g., Li et al., 2019; Sun et al., 2012), we also consider the role played by sex in PIU trajectories.

Loneliness. The Cognitive-Behavioral Model of PIU has long identified loneliness as a key momentary driver of PIU (Davis, 2001), which is purported to alleviate loneliness perceptions when they occur. More precisely, loneliness is generally defined as a momentary negative psychological experience characterized by a lack of satisfying interpersonal relationships and the perceived inadequacy of one's social network (Russell et al., 1980). Research has generally revealed positive associations between loneliness and PIU (e.g., Zhang et al., 2018), consistent with the idea that the Internet might provide lonely people with a way to break out, even if only temporarily and virtually, of their social isolation. Indeed, the Internet makes it possible for lonely people to interact with others, to widen their social network, and to experience a temporary sense of belongingness. This proposition has been empirically supported by Song et al. (2014), who reported positive associations between loneliness and using the Internet for social purposes. Caplan (2003) further argued that lonely individuals might perceive themselves as less socially competent, which in turn leads them to prefer computer-mediated interactions relative to face-to-face communication, which in turn might reinforce these negative impressions. However, on the Internet, lonely individuals tend to be more open and friendlier (Huan et al., 2014), which might further reinforce their Internet use behaviors. In the present study, we seek to refine our understanding of these associations by investigating whether and how they would generalize longitudinally via a consideration of loneliness as a time-varying predictor of PIU trajectories.

Perceived parenting behaviors. The Cognitive-Behavioral Model of PIU (Davis, 2001) emphasizes the lack of social support in the development of PIU. Within the social environment, several studies (e.g., Li et al., 2014) have emphasized the critical role played by parents in adolescents' lives and PIU development. The present study seeks to expand on prior research by considering the role of two key parenting behaviors as possible antecedents of adolescents' PIU trajectories: parental care and neglect. Parental care refers to the expression of warmth, empathy, interest, and closeness (Parker et al., 1979), while parental neglect refers to the intentional or unintentional unavailability or unresponsiveness to adolescents' needs or attention (Glaser, 2002).

Prior studies have suggested that a suboptimal parent-child relationship (i.e., low care and/or high neglect) might partly be responsible for adolescents' higher levels of PIU (Kalaitzaki & Birtchnell, 2014). Adolescents might turn to the Internet and become absorbed by it because it provides them with a substitute for suboptimal relationships. Empirical studies have reported support for the importance of parents in relation to PIU as parental neglect have been positively associated with PIU (e.g., Hsieh et al., 2016).

In contrast, better parent-child relationships (Shek, Zhu, et al., 2019) have been found to be negatively associated with PIU. Parental knowledge, which bears conceptual similarities with parental care (Omer et al., 2016), have also been identified as a key predictor of PIU (Ding et al., 2017). These results thus suggest that more adequate parenting practices may facilitate the internalization and transformation of parental care into self-care (Omer et al., 2016). This, however, might not be the case for parental neglect. Indeed, rather than reflecting voluntary desirable or undesirable actions enacted by the parents in a volitional manner, neglectful parenting rather refers to a lack of desirable actions, which might in turn prevent adolescents from internalizing parenting practices (Ryan & Deci, 2017).

An important limitation of previous studies examining associations between PIU and perceived parenting behaviors is the lack of differentiation between maternal and paternal practices, even though mothers and fathers are known to play a distinct and complementary role in adolescent development and adolescents are known to interact differently with each of their parents (Steinberg, 2001). Xin et al. (2018) reported that maternal, but not paternal, neglect positively predicted adolescents' PIU. Xu et al. (2014) also showed that PIU was more strongly related to the mother-child relationship than to the father-child relationship. In the present study, we expand on these previous studies by considering the role of maternal and paternal care and neglect as possible predictors of youth longitudinal PIU trajectories.

Various theoretical perspectives on parenting assumes that these parental behaviors tend to remain highly stable over the course of adolescence (e.g., Baumrind, 1989; Darling & Steinberg, 1993). Supporting this assertion, these behaviors have been shown, across a variety of studies relying on diverse methodologies, to remain highly stable over the course of development for a majority of individuals (e.g., Rimehaug et al., 2011; Zhou et al., 2002). For these reasons, parenting behaviors were treated as time-invariant predictors (measured only at Time 1) in the present study.

Sex. The Internet Availability Hypothesis (Su et al., 2019) suggests that Internet availability and usage tends to be higher among males relative to females, thus suggesting that PIU levels might also be higher among males relative to females. In addition, personality theories emphasize that males tend to be more impulsive (Cross et al., 2011) which is a known determinant of addictive behaviors (Lee et al., 2019) such as PIU. However, empirical results regarding associations between sex and PIU have been mixed, suggesting the need for further investigations. Thus, a first group of studies reported a lack of sex-related differences in PIU (van der Eijnden et al., 2008). A second group of studies reported higher PIU scores for girls relative to boys (e.g., Sun et al., 2012). Finally, a third group of studies reported higher PIU scores for boys compared to girls (e.g., Li et al., 2019). Importantly, most previous studies have failed to consider possible sex differences related to the shape of PIU trajectories as they unfold over time. We were able to identify a single study (Li et al., 2019) reporting that boys had higher initial levels of PIU and that boys also had a faster declining rate of change. However, this particular study only focused on a 6-month period which precludes drawing conclusions over a longer period of time. The present study seeks to extend these initial results to the consideration of a longer time period (i.e., 3 years).

Outcomes of Problematic Internet Use

Some consequences of PIU have already been identified in prior research. For instance, PIU has been negatively linked with cognitive functioning (Park et al., 2011), while being positively associated with self-injurious behaviors (Lam et al., 2009). In the present study, we focus on depressive symptoms, substance use, and academic achievement as a complementary set of outcomes that are able to provide a more detailed picture of the potential negative consequences of PIU trajectories.

Depressive symptoms. Depression has been identified as a highly prevalent mental disorder with a point-prevalence of 4-5% in mid-to-late adolescence (Thapar et al., 2012). Depression encompass a variety of symptoms, including depressive mood, anhedonia, impaired concentration, and feelings of guilt and worthlessness (American Psychiatric Association, 2013). Depressive symptoms have been found to be related to a variety of undesirable outcomes such as weakened immune system (Reiche et al., 2004). Generally, research has revealed small-to-moderate positive associations between depressive symptoms and PIU (e.g., Liang et al., 2016), consistent with the idea that individuals with PIU tend to experience higher levels of negative emotions (Kandell, 1998). However, this observation of time-specific correlations is not fully consistent with the compensatory model of internet addiction (Kardefelt-Winther, 2014), as well as with the developmental model of addiction (Brand et al., 2016, 2019), which both propose that addictive behaviors initially emerge as a way to alleviate negative feelings by generating compensatory positive emotions. However, both models also note that, over time, these benefits in terms of mood regulation should fade away and be replaced by negative consequences. These negative consequences are typically ascribed to the excessive amount of time spent on the Internet by problematic users, which decreases the amount of time they are able to spend on other pleasant activities, to maintain contact and interact with loved ones, or to engage in any other relevant, meaningful, and protective activities (Brand et al., 2016, 2019; Kardefelt-Winther, 2014). These restricted opportunities to proactively invest in other life domains are likely to lead to diminished mental health. This explanation fits well with the Dualistic Model of Passion (Vallerand, 2015) which states that obsessive passion tends to be associated with negative consequences (e.g., depression) due to its all-encompassing nature. This proposition has been supported by longitudinal studies reporting negative associations between PIU and mental health (Ciarrochi et al., 2016; van der Eijnden et al., 2008).

Substance use. Substance use is another severe health-related issue that tends to increase during adolescence, which has been explained by the normative risk-taking, novelty-seeking exploration behaviors characterizing adolescence (Spear, 2000). Substance use has been highlighted as an increasingly important issue around the world (ESPAD Group, 2016), given the increasing number of adolescents who experience with alcohol, tobacco, or drugs. The comorbidity hypothesis (Cheng et al., 2018) positions PIU as a type of pathology or addiction likely to be associated with a variety of other psychosocial problems, including other forms of involvement with addictive materials such as substance use, due to their shared neurobiological mechanisms. Moreover, PIU has also been shown to result in various forms of interpersonal impairments, likely to further increase the risk of increased PIU level (Cheng et al., 2018), but also of other forms of addictive behaviors (Stickley et al., 2014). Indeed, PIU has been positively associated with alcohol use (Ko et al., 2008), and other forms of substance use (Liu et al., 2011). These associations can be partly explained by the self-medication model (Khantzian, 1997), proposing that adolescents might start using various substances (e.g., alcohol, smoking, drugs) as a way to cope with the high level of negative feelings and emotions accompanying PIU.

Academic achievement. Our focus on academic achievement as a final important outcome of PIU trajectories is intimately related to the fact that schools are a key life area for adolescents, such that academic achievement comes to reflect adolescents' independent success outside of the family setting. A key indicator of academic success, academic achievement is often operationalized in the form of grade point average (GPA). GPA itself is highly important for adolescents' academic trajectories as most post-secondary institutions anchor admission decisions on adolescents' secondary school GPA. High school GPA is also predictive of educational attainment and earnings in adulthood (French et al., 2015). The digital Goldilocks hypothesis (Przybylski & Weinstein, 2017) suggests that moderate technology use is not harmful, but extensive forms of time-intensive engagement in online activities, which characterizes PIU, is likely to replace time that adolescents should instead dedicate to their academic activities. As such, higher levels of PIU should lead to reduced levels of academic achievement. Accordingly, research has generally reported moderate negative associations between PIU and GPA (Stavropoulos et al., 2013).

Bidirectional relations between PIU and outcomes. Even though our treatment of depressive symptoms, substance use, and academic achievement as outcomes (rather than predictors) was rooted in theory, we need to acknowledge the equally plausible role of these variables as predictors for PIU trajectories. For instance, the theory of compensatory Internet use (Kardefelt-Winther, 2014) suggests that some individuals might use the Internet excessively in order to cope with negative life situations (i.e., having low grades in school) as well as to escape from their negative emotions (i.e., having a depressed mood). In both cases, the unhealthy motivation of escapism might drive adolescents toward PIU, suggesting that higher levels of depressive symptoms and lower levels of academic achievement might also lead to a greater tendency to rely on PIU. Regarding substance use, Jessor's (1991) model of risky behaviors posits that presenting one risky behavior (e.g., substance use) is also likely to represent a risk factor for other risky behaviors (e.g., PIU). Consequently, it is possible for prior higher substance use to predict subsequent higher PIU.

The Present Research: Hypotheses and Expected Contributions

The present study was designed to help improve our understanding of PIU development during late adolescence. In addition, to better understand the implications of inter-individual differences related to these longitudinal trajectories, we also assessed their relations with theoretically-relevant predictors (loneliness, perceived parenting behaviors, sex) and important outcomes (depressive symptoms, substance use, academic achievement).

Based on the reviewed research literature, our first hypothesis (Hypothesis 1) states that PIU will demonstrate moderately stable trajectories over time, and that these trajectories will display a significant level of inter-individual variability. However, in the absence of clear empirical evidence upon which to anchor our expectations, we leave as an open research question whether these trajectories will display a normative increase or decrease over time. In relation to predictors, and based of previous empirical evidence, we expected loneliness (Hypothesis 2) and parental (both maternal and paternal) neglect (Hypothesis 3) to positively predict PIU. Likewise, we expect parental (both maternal and paternal) care (Hypothesis 4) to negatively predict PIU, and boys to present higher levels of PIU relative to girls (Hypothesis 5). From an outcomes perspective, we expected PIU trajectories to be associated with higher levels of depressive symptoms (Hypothesis 6a) and substance use (Hypothesis 7a), as well as with lower levels of academic achievement (Hypothesis 8a). However, we also expected depressive symptoms (Hypothesis 6b), substance use (Hypothesis 7b), and academic achievement (Hypothesis 8b) to reciprocally predict PIU trajectories.

The present study was designed to achieve four main contributions. First, we focus on PIU trajectories as they unfold over three years among a sample of late adolescents entering early adulthood, allowing us to support the formulation of a more formal theoretical developmental model aligned with this critical developmental period. This consideration is important. Indeed, only limited research attention has been paid to late adolescents and emerging adults, relative to younger children and adolescents. However, substantial developmental and socioemotional changes occurring during this key developmental period are likely to have lasting effects for the rest of adult life (Piotrworski & Valkenburg, 2015). In this context, it is to be expected that PIU habits formed during this period should be more likely to persist into adulthood (Hurd et al., 2014; Valkenburg & Peter, 2013).

Second, this study contributes to our understanding of PIU by relying on a latent change approach for the outcomes, allowing for a more accurate way of controlling for baseline levels and making it possible to assess the effects of PIU trajectories on longitudinal change in outcome levels for the first time in this research area. Third, this study examines the directionality of the relations occurring between PIU and the outcomes, thus contributing to our understanding of PIU by comprehensively establishing (for the first time also) the directionality (and possible reciprocity) of these associations. Fourth, by incorporating individual and social antecedents, this study extends previous studies by investigating the time-invariant effects of sex, paternal care and neglect, and maternal care and neglect, as well as the time-varying effects of loneliness to clarify their relative contribution to PIU.

Method

Participants and Procedure

The present study relies on the High School Cohort of the Bridging the Gaps and Mind-the-Gap longitudinal study conducted between 2013 and 2015 and involving the annual participation of public schools located in the city of Helsinki, Finland (Mind the Gap and Bridging Gap, 2014). This cohort of participants was recruited in their first year of high school with the goal of studying adolescents who have socialized and grown up in the era of information and communication technologies (ICTs; Mind the Gap and Bridging Gap, 2014). Questionnaires were administered during school hours and completion took approximately an hour. Participation was voluntary and both parents and students provided active consent beforehand. Ethical approval was obtained from the University Ethics Committee.

The present study focuses on the 1736 adolescents (65.7% female) from this cohort who were surveyed in 2013 (Time 1: aged 16-17 years), in 2014 (Time 2: aged 17-18 years), and 2015 (Time 3: aged 18-19 years). Most participants were born in Finland (93.4%) with Sweden, Russia, Estonia, Somalia, and other countries also being reported as countries of birth. Similarly, 90.3% reported Finnish as their maternal language with Swedish, Russian, Estonian, Somali and other languages also being reported. Half of the participants (66.2%) lived with their parents at the time of the initial data gathering and most participants reported that their fathers (93.4%) and mothers (91.3%) were employed at that time.

Measures

Problematic Internet Use (PIU). Participants' PIU were assessed at all time points using a 5-item scale (e.g., "I have powerful urge to use ICT all the time"; α_{T1} = .833, α_{T2} = .821; α_{T3} = .805). This scale was developed in Finnish by Kaltiala-Heino et al. (2004). Items were rated on a 7-point scale (1 = completely disagree, 7 = completely agree). Evidence supporting its psychometric properties have been reported by Salmela-Aro et al. (2017).

Loneliness. Loneliness was measured at all time points using an 8-item version (e.g., "I would like to have more friends"; α_{T1} = .822, α_{T2} = .845; α_{T3} = .849) of the UCLA Loneliness Scale Version 3 (Russell, 1996; Finnish version by Salmela-Aro, & Nurmi, 1996). Items were rated on a 4-point scale (1 = never, 4 = often). Evidence supporting its psychometric properties have been reported by Nurmi and Salmela-Aro (1997) and Nurmi et al. (1997).

Perceived Parental Behaviors. At Time 1, adolescents reported their perceptions of the caring (3 items for each parent, e.g., "My mother has supported me in my own decisions"; α_{mother} = .846; α_{father} = .873) and neglectful (2 items for each parent, e.g., "My mother doesn't have time to think about my things"; α_{mother} = .803; α_{father} = .823) behaviors used by their parents using a scale developed in Finnish by Duineveld et al. (2017). These items were rated on a 7-point scale (1 = not at all true, 7 = completely true). Evidence supporting the psychometric properties of these measures have been reported by Duineveld et al. (2017).

Depressive symptoms. At Time 1 and 3, depressive symptoms were assessed using the 10-item Finnish Depression Scale (DEPS-10; Salokangas et al., 1994), focusing on adolescents' mood during the previous month (e.g., "I felt like everything needed an effort"; α_{T1} = .892; α_{T3} = .926). Items were rated on a 4-point scale (1 = not at all, 4 = very much). Evidence supporting its psychometric properties have been reported by Wang et al. (2015).

Substance Use. At Time 1 and 3, substance use was measured with 3 items from the Finnish school health promotion study (National Institute for Health and Welfare, 2020) focusing on smoking (1 = once a day or more often; 2 = once a week or more often, but not daily; 3 = more rarely than once a week; 4 = currently not smoking or have quit smoking; 5 = I have tried smoking; 6 = I have never smoked), drinking (1 = once a week or more often; 2 = couple times a month; 3 = about once a month; 4 = more rarely; 5 = I have tried alcohol; 6 = I do not use alcohol), and using drugs (1 = never; 2 = once; 3 = 2-4 times; 4 = 5 times or more often). Items were reversed, higher scores reflect greater use (α_{T1} = .687; α_{T3} = .592). Evidence supporting its psychometric properties have been reported by Kiuru et al. (2010).

Academic achievement. Adolescents' academic achievement was measured via grade point averages obtained at Time 1 and Time 3 from school records.

Analyses

Model Estimation

All analyses were conducted with Mplus 8 (Muthén & Muthén, 2017) using the robust maximum likelihood (MLR) estimator while taking into account students' nesting within the classrooms and schools using Mplus design-based correction of standard errors (Asparouhov, 2005). Full Information Maximum Likelihood (FIML) was used to handle missing data. FIML allows the estimation of all models, even under high missingness conditions when missingness is conditioned on other variables in the model (Lee et al., 2019; Newman, 2003), using the full sample of 1736 participants who completed at least one measurement point without relying on a suboptimal deletion of participants who completed a single measurement point (Enders, 2010; Graham, 2009). Overall, 1335 participants participated at Time 1, 923 at Time 2, and 539 at Time 3. Of all participants, 520 completed one measurement point, 597 completed two measurement points, and 619 completed all three measurement points. Among those who participated at each time point, missing data was low (Time 1: 0% to 4.12%, M = 1.25%, SD = 1.35%; Time 2: 0% to 2.60%, M = 1.63%, SD = 1.13%; Time 3: 0% to 1.48%, M = .91%, SD = .35%). Attrition analyses are reported in Table S6 of the online supplements.

Preliminary Measurement Models

Preliminary measurement models were first estimated to confirm the factor structure and psychometric adequacy of the measures used in this study. Due to the complexity of the longitudinal measurement models underpinning all constructs considered in the present study, four distinct sets of measurement models were estimated using confirmatory factor analyses (CFA). First, PIU was modelled as a one-factor CFA model. Second, loneliness was modelled the same way, but one a priori correlated uniqueness (CU) was added to control for the negative wording of two items (Marsh et al., 2010). Third, perceived parental behaviors were modelled using a four-factor CFA model representing paternal care, maternal care, paternal neglect, and maternal neglect. In this model, a priori CUs were included to account for the methodological artefact associated with the parallel wording of the items measuring paternal and maternal behaviors (Morin et al., 2020). Neglect was measured using two items, creating a locally underidentified factor (even though the model remains globally identified). To address this issue, essentially tau-equivalent constraints (ETECs; Little et al., 1999) were used to achieve the local identification of these two factors by putting equality constraints on the factor loadings, thus assuming that both items represented equivalent indicators of the underlying factor. Finally, the multi-item outcomes were represented as a CFA including two factors (substance use and depressive symptoms).

Because PIU and loneliness were measured at all three time points, and because we controlled for Time 1 levels of the outcomes, we verified via tests of longitudinal measurement invariance that the definition of these constructs remained unchanged over time. In these models, factors were allowed to correlate across time points, and a priori CUs were included between matching indicators at different time points to avoid inflated stability estimates (Marsh, 2007). Tests of measurement invariance were conducted in the following sequence (Millsap, 2011): (1) configural invariance; (2) weak invariance; (3) strong invariance; (4) strict invariance; (5) latent variance-covariance invariance; and (6) latent means invariance. For loneliness we verified the invariance of the correlated uniquenesses. Factor scores were saved from these preliminary models for the main analyses. Factor scores provide a partial control for unreliability by giving more weight to more reliable items and preserve the measurement structure (e.g., invariance) better than scale scores (Morin et al., 2016). We calculated model-based composite reliability indices (ω; McDonald, 1970).

Latent Curve Models

All analyses conducted in the present study were specifically designed to test the hypotheses presented earlier. As such, these analyses can all be considered to be confirmatory in nature. To this end, latent curve models (LCM; Bollen & Curran, 2006) were used to represent adolescents' growth trajectories of PIU. In these analyses, time-specific measures of PIU were factor scores saved from the model of strict measurement invariance estimated previously. Consistent with a linear LCM parameterization, two growth factors were estimated: (1) an intercept factor, reflecting the average initial level of PIU across all participants, and inter-individual variations around this average level; and (2) a slope factor, reflecting the average amount of change per unit of time across all participants, and inter-individual variations around this average level of change. In accordance with typical linear LCM parameterizations (Bollen & Curran, 2006), the factor loadings of the repeated measures on the intercept factor were all set to be 1, whereas their factor loadings on the slope factors was set to be 0-1-2 to reflect the passage of time as a function of the one-year time intervals between each measure.

Loneliness was incorporated as a time-varying predictor and was represented using an autoregressive cross-lagged parameterization in which (1) freely estimated autoregressive paths were specified between the repeated measures of loneliness; (2) freely estimated cross-lagged path were specified between loneliness at a specific point in time and the PIU indicator measured at the subsequent point in time; and (3) freely estimated time-specific correlations were specified between loneliness and

PIU indicators within each time wave.

Paternal/maternal care and neglect, and sex were incorporated to the model as time-invariant predictors, and allowed to predict the intercept and slope factors of the PIU trajectories. Likewise, baseline (Time 1) levels of depressive symptoms, substance use, and academic achievement were also allowed to predict the intercept and the slope factors of PIU. Finally, to assess changes in the outcomes due to the intercept and slope factors, latent change models (McArdle, 2009) were estimated for depressive symptoms, substance use, and academic achievement. Latent change models made it possible to disaggregate the repeated measures of participants' depressive symptoms, substance use, and academic achievement into their initial levels (the Time 1 scores) and a latent change factor representing decline or growth occurring between Time 1 and Time 3. These change factors were specified as predicted by the intercept and the slope factors of the PIU trajectories. Relying on the latent change approach provided a more explicit way of controlling for baseline levels, while also allowing us to more rigorously test the effects of the PIU trajectories on change occurring over time in the outcomes (see Appendix 1 in the online supplements for specifications). The LCM model including all predictors and outcomes is graphically depicted in Figure 1.

Model Assessment

Model fit was evaluated using goodness-of-fit indices (Marsh et al., 2005), including the comparative fit index (CFI), the Tucker-Lewis Index (TLI) and the root mean square error of approximation (RMSEA) with its 90% confidence interval (CI). For the CFI and TLI, values above .90 reflect adequate fit, while values above .95 reflect excellent fit. For the RMSEA, values below .08 reflect adequate fit and values below .06 reflect excellent fit. For purposes of model comparisons, relative changes (Δ) in the fit indices were inspected with a change of at least .010 for CFI and TLI and a change of at least .015 for the RMSEA were taken to suggest meaningful differences (Cheung & Rensvold, 2002; Chen, 2007).

Results

Preliminary Measurement Models

Model fit for the measurement models is reported in Table 1, and show that all models were able to achieve an adequate level of fit to the data (all CFI/TLI $\geq$ .90 and all RMSEA $\leq$ .06). The longitudinal models underpinning the measurement of PIU, loneliness and outcomes demonstrated invariance over time (ΔCFI and ΔTLI $\leq$ .01; ΔRMSEA $\leq$ .015), with the exception of one item intercept that had to be freed in all three models to achieve partial strong invariance, and one uniqueness that had to be freed in the outcomes model to achieve partial strict invariance. Parameter estimates associated with these measurement models are reported in Tables S1, S2, S3 and S4 of the online supplements. Overall, the results revealed well-defined reliable factors for PIU (λ = .510 to .837; ω = .829), loneliness (λ = -.324 to .777; ω = .839), paternal care (λ = .783 to .916; ω = .873), paternal neglect (λ = .795 to .893; ω = .834), maternal care (λ = .733 to .932; ω = .856), maternal neglect (λ = .774 to .876; ω = .812), depressive symptoms (λ = .408 to .809; ω = .909), and substance use (λ = .578 to .816; ω_{T1} = .732, ω_{T3} = .710). Correlations among the factor scores derived from these measurement models are reported in Table S5, and show that PIU was negatively related to paternal and maternal care and positively to paternal and maternal neglect. PIU was also positively associated with loneliness, depressive symptoms, and substance use, while showing weaker negative associations with sex and academic achievement.

Latent Curve Models

Goodness-of-fit for the LCMs are reported in the lower section of Table 1, supporting the adequacy of the unconditional linear LCM model. Parameter estimates from this model are reported in Table 2, revealing an intercept factor that is significantly higher than 0 (3.675, considering that PIU item are scored on a 1 to 7 scale), consistent with moderate normative levels of PIU in the total sample at the beginning of the study, but which also displayed a substantial level of inter-individual variability (with a variance of .827, corresponding to a SD of .909 units). In addition, these results also revealed a statistically significant decreasing linear slope, consistent with the presence of a small average decline in PIU levels of .038 units per annum, but which also displayed significant inter-individual variability (i.e., with a variance of .038, corresponding to a SD of .195 units). The correlation between these two growth factors was negative and moderate (r = -.465), suggesting that adolescents with higher initial PIU levels tended to present steeper declines. The examination of the time-specific residuals showed that the growth factors provided a satisfactory depiction of the repeated PIU measures with the proportion of explained variance ranging from 66.9% to 100%.

The predictors and outcomes were then incorporated to this unconditional LCM model resulting in an adequate level of fit (see Table 1). Adding equality constraints on the longitudinal associations between the PIU measures and the repeated measures of loneliness result in a negligible change in model fit, consistent with the longitudinal stability of these associations. The examination of parameter estimates from this model, reported in Table 3, showed that prior loneliness scores positively predicted PIU at the subsequent time point. The intercept factor of the PIU trajectories was positively predicted by being male and paternal neglect, and depressive symptoms, and negatively predicted by maternal care. However, the slope factor was only negatively predicted by depressive symptoms. Turning our attention to the outcomes: (a) the intercept factor predicted decreases, but the slope factor predicted increases in depression; (b) increases in substance use were positively predicted by the intercept factor, but not by the slope factor; and (c) both the intercept and the slope factors of PIU predicted decreases in academic achievement.

Discussion

Interest in PIU has been continuously increasing over the past decades because of its prevalence and its detrimental effects (e.g., Kuss et al., 2014). Internet gaming disorder, which bears some conceptual similarities with PIU, was conditionally included in the latest edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5; American Psychiatric Association, 2013) and was proposed to be included in the upcoming International Classification of Diseases (ICD-11; World Health Organization, 2018). These policy-making decisions highlight the importance of more rigorously examining the development of PIU in order to better understand how it emerges and fluctuates over time, which in turn can help practitioners to devise interventions seeking to curb its emergence. The present study thus investigated the development of PIU over three years during late adolescence, as well as its social and individual antecedents and outcomes.

Our findings revealed moderate average levels of PIU at the initial time of measurement (3.676 on a 1 to 7 scale), followed by a slight decline over the subsequent three years. This result matches prior research showing that PIU levels remain moderately stable over the course of adolescence (van den Eijnden et al., 2008), and tend to be characterized by a slight short-term (i.e., six months) decrease (Li et al., 2019) in early-to-middle adolescence. Our study complements these findings and adds another piece to the puzzle by showing that PIU decreases in late adolescence as well. When coupled with these previous observations, the present results suggest that adolescence might be characterized by moderate PIU levels that tends to decrease over time as one passes from early to late adolescence and that seems to persist into early adulthood. A similar type of longitudinal trajectory has been identified for obsessive passion, whose ongoing development toward becoming a lifelong habit seems to be relatively slow (Tóth-Király, Bőthe, Jánvári, et al., 2019; Vallerand et al., 2015), providing various opportunities to turn back toward more normative types of activity involvement. The normative decline identified here suggests that many youths might come to progressively allocate less time to Internet as part of their normative maturation process, whereas some others will tend to persist toward a more chronic type of involvement.

Several theoretical reasons might help to understand this phenomenon. First, personality theories suggest that, as part of the normative maturation that accompanies the transition between late adolescence and early adulthood, youth typically tend to become more disciplined and self-regulated (Caspi et al., 2005; Roberts et al., 2001). Second, developmental theories state that late adolescents and early adults are typically faced with a variety of developmental challenges and decisions (e.g., continue their studies in higher education or rather to pursue a vocational career) that set the stage for their continued development (Zarrett & Eccles, 2006). However, regardless of the choices that they make during this period, youth will still generally need to invest efforts into their academic work in order to reach most of these goals, thus taking away time from non-essential Internet-related activities. Likewise, the first romantic relationships tend to develop during adolescence (Meier & Allen, 2008) which might take adolescents' attention away from other areas. Third, the brain areas believed to be responsible for cognitive and inhibitory control might become more developed in adolescence (Casey et al., 2005), suggesting that youth might become gradually better at regulating their behavior. All these might contribute to the slight normative decline in PIU observed in this study. By allowing us to bridge the gap between what happens earlier, and later, in development, the current results appear to set the stage for future theoretical developments helping us to better understand the lifelong process via which PIU emerges, evolves, and stabilizes over time. The fact that the observed trajectories seems to share connections with theoretical perspectives used to guide research in other research areas (e.g., passion, personality, development, neurosciences) appears to set the stage for the development of a more comprehensive theoretical model of PIU development.

Importantly, substantial inter-individual variability was observed in relation to the shape of these trajectories. This variability reveals that PIU trajectories might be much higher for a subset of adolescents, and reinforces that not all adolescents experience a similar decreasing trajectory. This observation provides a potential explanation for the divergent results reported by Ciarrochi et al. (2016) showcasing increasing PIU trajectories during high school. Since LCMs synthesize individual trajectories into a single sample-average trajectory, PIU might be in fact decreasing for some participants but increasing for others, yet still leading to an overall increasing sample average. These observations reinforce the need to better understand factors involved in the prediction of PIU, and the outcomes implications of PIU trajectories.

Social and Individual Antecedents of PIU

From a theoretical perspective, the Cognitive-Behavioral Model (Davis, 2001) positions the social environment as a key determinant of PIU. Adopting this model, the present study focused on the predictive role of loneliness and perceived parenting behaviors in relation to PIU trajectories. Our results supported Hypothesis 2 and were convergent with previous research results reporting positive associations between loneliness and PIU. These associations were found to generalize over the three years of the study, showing that time-specific levels of loneliness systematically predicted higher levels of PIU at the next time point over and above student-specific loneliness trajectories. Lonely or isolated individuals, because of an insufficient degree of satisfaction of their need for relatedness, might be more likely to turn to the Internet in order to compensate for this perceived isolation and find an alternative way of fulfilling their needs for relatedness (Vansteenkiste & Ryan, 2013) and of coping with the negative emotions known to be associated with loneliness (Bastian et al., 2015). Prior empirical research has already provided support for this assertion (Jun & Choi, 2015). The relative ease with which Internet can be used to such end while remaining physically isolated, relative to real-life social contacts, might in turn explain why this use carries a risk of becoming excessive or problematic. Indeed, Internet use might allow isolated users to overcome their perceived social incompetence (Caplan, 2003) and develop social relations with others in a "safer" online environment. By this, the Internet might allow "the poor to get rich" in terms of social connections (Ellison et al., 2007).

Previous studies have highlighted the relevance of perceived parenting practices with respect to PIU (e.g., Li et al., 2014). The present study provided support for these results by showing that maternal and paternal practices differentially predicted PIU. However, Hypotheses 3 and 4 were only partially supported as maternal (but not paternal) care was found to predict lower initial levels of PIU, and paternal (but not maternal) neglect was found to predict higher initial values of PIU.

These findings, aligning with prior studies (e.g., Shek, Zhu, et al., 2019), highlight the adaptive role of having a good parent-child relationship in relation to PIU. Mothers' perceived caring behaviors negatively predicted PIU, suggesting that expressing warmth and interest toward adolescents and cultivating a quality relationship with them might decrease their need to seek solace in PIU. As it becomes progressively internalized into their identity, caring maternal behaviors may gradually give rise to more optimal self-care behaviors during this developmental period (Omer et al., 2016), thus helping adolescents to more efficiently self-monitor their Internet usage without the need for external regulators.

Conversely, results pertaining to paternal neglect and PIU echo earlier empirical findings (e.g., Hsieh et al., 2016). Experiencing a lack of involvement, guidance, and a high degree of permissiveness from their fathers seemed to hinder adolescents' ability to set healthy personal boundaries for themselves (Liu & Potenza, 2007). Via neglectful parental behaviors, fathers might provide too much freedom and fail to establish rules that could help to limit the internalization of the self-regulatory skills necessary to limit the emergence of PIU. This proposition is supported by studies in which having fewer parental constraints was positively associated with self-regulatory deficits in early childhood (Piotrowsky et al., 2013).

The fact that different maternal and paternal behaviors predicted PIU highlights the more fine-grained differences between these two sources of social support. It appears that paternal neglect and maternal caring behaviors are important with respect to PIU. These results are consistent with those of Shek et al. (2018) and Yao et al. (2014), who reported that mothers and fathers have a different impact on adolescents' PIU. The present study adds to the literature by showing that fathers' and mothers' perceived caring and neglectful behaviors predicted PIU differently, supporting the notion that parental effects should be distinguished and investigated separately. Still, future studies are needed to verify these conclusions.

These effects seem stable over time, with no additional relations observed between youth parenting perceptions and the slope of their PIU trajectories. This observation is aligned with the idea that parenting practices create some form of relatively stable household climate with which youth may come to cope via a variety of ways, including the Internet, rather than a more dynamic predictor of fluctuations in PIU levels. This interpretation is, however, limited by our consideration of parenting practices as time-invariant predictors. Future research would do well by testing these associations using more dynamic (i.e., time-varying) measures of parenting behaviors to better understand their time-structured associations with PIU.

Finally, with respect to adolescents' sex, our results showed that boys tended to present higher initial levels of PIU than girls, supporting Hypothesis 5. This result matches those observed in earlier studies (e.g., Li et al., 2019). Importantly, a recent meta-analysis (Su et al., 2019) of 101 published studies having reported sex-related differences in PIU showed that males are more likely to have a higher level of PIU than females. This result might be explained by the fact that, in general, girls tend to be less prone to exhibit addiction-like behaviors such as PIU (Minutillo et al., 2016) and be less impulsive (Cross et al., 2011) relative to males who, according to the Internet Availability Hypothesis (Su et al., 2019) might also be more numerous to use Internet. Additionally, males might find a greater number of activities or functions on the Internet to engage in. Dufour et al. (2016) reported that males were intensively (i.e., more than 20 hours a week) engaged in watching YouTube videos, MMORPG and other online games, and visiting adult sites. By contrast, females were reportedly more intensively engaged in chatting and using social media.

Outcomes of PIU

Finally, the present research also documented the consequences of PIU in relation to depressive symptoms, substance use, and academic achievement, while also considering the possible reciprocal effects of these variables on PIU. Our results pertaining to depression partly matched our a priori expectations (Hypotheses 6a and 6b), highlighting a complex interplay between PIU and depression. First, initial levels of depression (antecedent) were related to higher initial levels of PIU, as well as to decreases over time in PIU trajectories. These results suggest that initial levels of depression (antecedent) might play two opposite roles in relation to PIU. First, they might orient adolescents toward excessive Internet use (higher initial levels) as a way to escape their negative mood. This observation is consistent with the compensatory model of Internet addiction (Kardefelt-Winther, 2014), which suggests that internet can be initially used a way to cope with negative feelings. Second, initial levels of depression may also predict decreases over time in PIU levels due to the fact that depressed individuals might lack energy to maintain this intensive level of internet engagement over a prolonged period of time (American Psychiatric Association, 2013).

In turn, higher initial levels of PIU predicted decreases in depression levels over time (outcome), whereas increases in PIU predicted increases in depression (outcome). The first of those observations suggests that initially high levels of PIU might be able to provide some lasting relief from depressive symptoms, possibly by providing a way to break down the initial cycle whereby emerging depressive symptoms, if left unchecked, evolve toward a more chronic pathway. Our results suggest that initial involvement in PIU might help to break down this cycle. This interpretation seems to match Brand et al.'s (2016, 2019) developmental model of addiction, which suggests that people tend to experience positive consequences (e.g., reduced depressed mood) in the early stages of addictions. However, the maladaptive role played by PIU becomes more apparent over time, as further increases in PIU seem to be accompanied by increases in depressive symptoms (outcome). This thus suggest that, despite the initial benefits of initial levels of PIU, these benefits will be offset when PIU keeps on increasing over time in an unchecked manner. This effect is likely to be explained by the other negative consequences associated with increased PIU levels (e.g., reduction in other pleasant activities and social contacts). This observation corresponds to both the compensatory model of Internet use (Kardefelt-Winther, 2014) and to the developmental model of addiction (Brand et al., 2016, 2019) suggesting that, despite initially pleasant effects, persistent addictive behaviors tend to generate undesirable consequences over time as users start to lose control of their involvement in the addictive activity.

Second, initial levels of PIU (but not increases over time in PIU levels) predicted increases in substance use, which is in line with our expectations (Hypothesis 7a) and previous research results (e.g., Ko et al., 2008) documenting high levels of comorbidity between PIU and substance use (Liu et al., 2011), leading to similar forms of addictions. Our results are also consistent with the self-medication model (Khantzian, 1997), suggesting that youth might come to use various substances (e.g., alcohol, smoking, drugs) as a way to cope with the negative feelings and emotions accompanying PIU. This association appears to be unidirectional as substance use did not predict PIU, thus failing to support Hypothesis 7b.

Finally, and in accordance with our expectations (Hypothesis 8a) and prior studies (e.g., Stavropoulos et al., 2013), initial levels of PIU and increases over time in PIU levels both predicted decreases in achievement levels over the course of the study. Presumably, adolescents who spend an unreasonable amount of time on the Internet may come to experience a reduced sleeping schedule, making it harder for them to properly rest and recharge (Alimoradi et al., 2019). This lack of rest in turn might lead to decreased attentional capacities and interest in learning, both of which are known to be associated with academic achievement (Kubey et al., 2001). Additionally, adolescents with PIU might also allocate less time to learning, studying, and homework, which could even more directly lead to declines in academic achievement. However, reciprocal effects were not observed between PIU and academic achievement, thus failing to support Hypothesis 8b, and suggesting the presence of unidirectional relationships going from PIU to academic achievement.

Practical Implications

Our results suggest that PIU is a malleable construct and that practitioners can take various approaches to tackle it. Several methods have been proposed to curb PIU such as motivational interviewing, cognitive behavioral therapy (CBT), counseling, positive youth development (Shek, Dou, et al., 2019), or inpatient care and retreat centers (Montag & Reuter, 2017). Some of these methods have already proven to be effective. A meta-analysis (Winkler et al., 2013) of 16 studies reported that both psychological and pharmacological interventions (e.g., multi-level counseling programs, reality therapy, and acceptance/commitment therapy) are effective for reducing PIU and associated characteristics such as depressive symptoms. These findings were reinforced by a more recent meta-analysis focusing on randomized-controlled trials (Malinauskas & Malinauskiene, 2019). School-based prevention programs are also promising (Throuvala et al., 2019).

Our results suggest that family-based interventions might also be effective. Based on our results, interventions (e.g., Webster-Stratton & Herman, 2010) should aim to help parents improve their interpersonal behaviors to demonstrate more caring and less neglectful behaviors, or at least find a balance in which emotional responsiveness is predominant, particularly for adolescents who otherwise feel lonely or socially isolated. Social belonging interventions might be useful against the experiences of loneliness (Walton et al., 2017). Our results also suggest that more attention should be paid to males given their potential higher risk of developing PIU. Finally, on a more global level, policymakers might wish to develop public health prevention campaigns raising awareness of PIU and highlighting the distinction between the optimal and suboptimal forms of Internet use.

Limitations

The shortcomings of our study should also be kept in mind when interpreting the results. We relied on self-reported questionnaires, which could be influenced by different self-report biases (e.g., social desirability). This limitation could be addressed in future studies through the administration of informant-reported measures obtained from peers, teachers, and parents. Furthermore, due to the need to rely on a Finnish version, some of the instruments used in the present study are not the most common measures generally used in the research literature, which limits our ability to compare our results with those form other studies, and reinforces the need for replication. Second, the present study relied on a three-year period. However, it would be interesting to examine how these results change over a more extended period of time, potentially following a sample from early adolescence into early adulthood. Third, the present study focused on PIU in general. It would thus be interesting for future studies to investigate the separate functions of Internet use (e.g., social media, adult content) to see whether the same mechanisms would generalize across functions.

Fourth, given that we relied on a sample of Finnish adolescents, conclusions about generalizability remain tentative. Future studies should be conducted in other countries. Fifth, causal conclusions cannot be drawn from our results. Sixth, although we were able to detect, and predict, the presence substantial inter-individual variability in the shape of the PIU trajectories, our analytic approach (LCM) did not allow us to identify subpopulations of adolescents characterized by qualitatively distinct growth trajectories. This limitation could be addressed by relying on growth mixture modeling. Seventh, despite our reliance on robust missing data procedures and the fact a majority of participants (70%) completed more than one time of measurement, our rates of missing data at the last time point (69%) remained high enough to reinforce the need for replication. Finally, as for the selection of our antecedents and outcomes, future research would do well to complement these findings with the inclusion of a more comprehensive set of predictors and outcome covering a more widespread set of life domains (school related predictors, types of social interactions with friends and teachers, etc.) and areas of functioning (academic, social, physical, etc.).

Conclusion

This study provided important insights into the nature and development of PIU by revealing normatively moderate level in late adolescence, while also demonstrating a slight linear decrease over time and substantial inter-individual variability. Reinforcing previous results regarding the detrimental effects of PIU for a variety of outcome variables, the present study further showed negative associations between PIU and adolescents' levels of academic achievement, and positive associations between PIU levels and adolescents' levels of depressive symptoms and substance use. In addition, depression reciprocally predicted PIU. However, and consistent with the idea that PIU might be malleable during adolescence, the present study also offers recommendations for the development of intervention strategies. Based on our results, PIU might be tamed by countering adolescents' sense of loneliness with meaningful relationships, and by putting more emphasis on optimal parenting practices.

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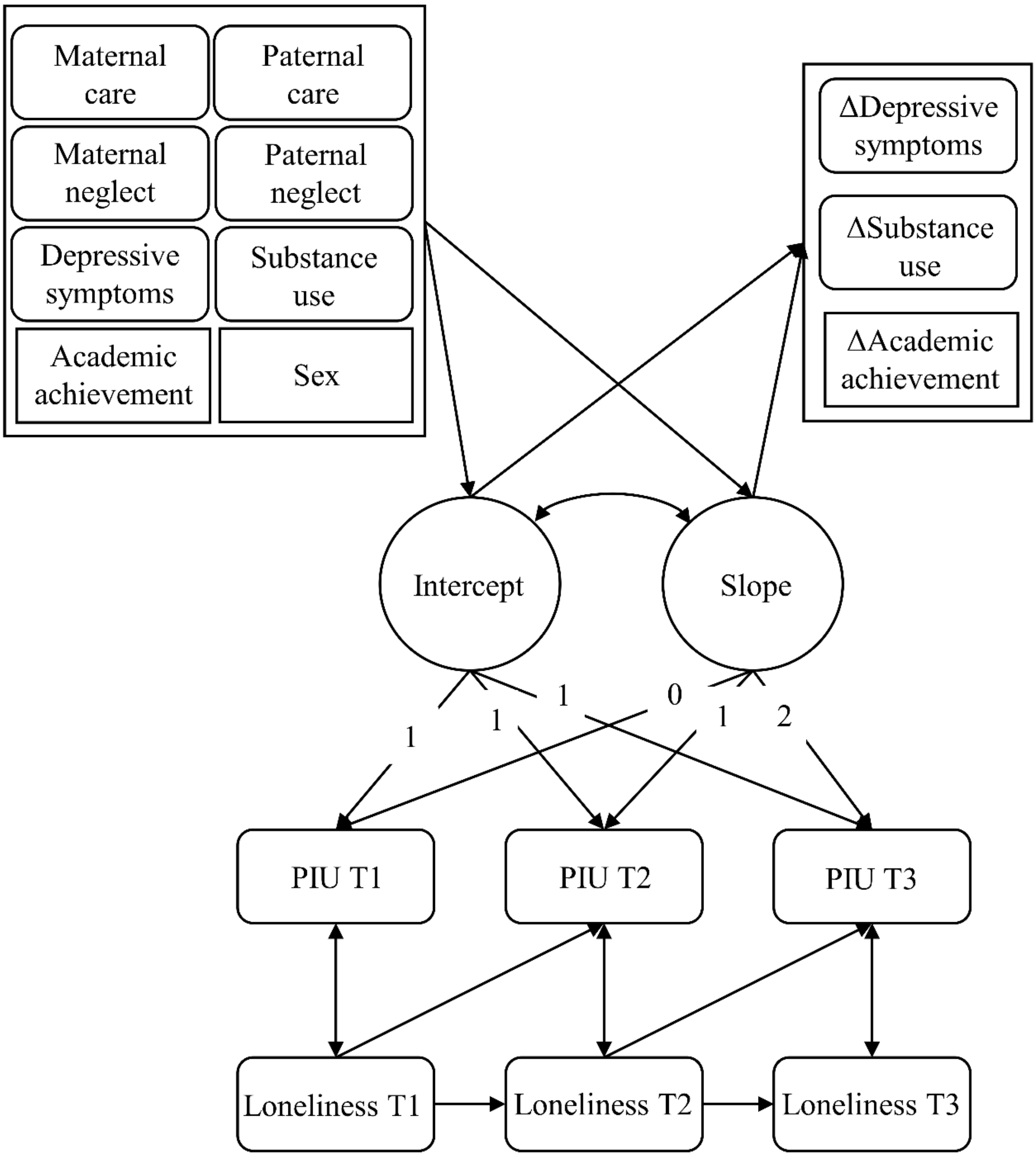

Figure 1

Schematic Representation of the Final Latent Curve Model

Note. PIU: problematic internet use; T1-T3: Time 1-Time 3. Ovals represent latent variables, squared with rounded corners represent factor scores derived from measurement models, and regular squares represent observed variables. Unidirectional arrows represent regressive paths, bidirectional arrows represent correlations. Delta (Δ) represents change over time.

Table 1

Goodness-of-Fit Indices Associated with the Estimated Models

Model	χ^2	df	CFI	TLI	RMSEA	90% CI	$\Delta\chi^2$	Δdf	ΔCFI	ΔTLI	ΔRMSEA
Problematic Internet Use											
Configural	225.261*	72	.969	.955	.035	[.030, .041]	—	—	—	—	—
Weak	256.363*	80	.964	.953	.036	[.031, .041]	31.432*	8	-.005	-.002	+.001
Strong	412.469*	88	.934	.922	.047	[.042, .051]	169.289*	8	-.030	-.031	+.011
Partial Strong	281.518*	87	.961	.952	.036	[.032, .041]	25.362*	7	-.003	-.001	.000
Strict	313.259*	97	.956	.953	.036	[.032, .041]	31.902*	10	-.005	+.001	.000
Latent Variance-Covariance	320.365*	99	.955	.952	.036	[.032, .041]	7.385*	2	-.001	-.001	.000
Latent Means	321.825*	101	.955	.954	.036	[.032, .040]	1.105	2	.000	+.002	.000
Time-Varying Predictor											
Configural	695.905*	222	.940	.926	.035	[.032, .038]	—	—	—	—	—
Weak	732.276*	236	.937	.927	.035	[.032, .038]	36.688*	14	-.003	+.001	.000
Strong	839.219*	250	.926	.918	.037	[.034, .040]	113.682*	14	-.011	-.009	+.002
Partial Strong	778.558*	249	.933	.926	.035	[.032, .038]	46.797*	13	-.004	-.001	.000
Strict	808.397*	265	.932	.929	.035	[.032, .037]	36.149*	16	-.001	+.003	.000
Correlated Uniquenesses	803.727*	267	.932	.930	.034	[.032, .037]	.727	2	.000	+.001	-.001
Latent Variance-Covariance	818.341*	269	.931	.929	.035	[.032, .037]	14.944*	2	-.001	-.001	.001
Latent Means	821.373*	271	.931	.929	.034	[.032, .037]	3.149	2	.000	.000	-.001
Outcomes											
Configural	1028.537*	280	.926	.915	.042	[.040, .045]	—	—	—	—	—
Weak	1055.792*	291	.925	.916	.042	[.039, .045]	29.481*	11	-.001	+.001	.000
Strong	1275.255*	302	.904	.897	.046	[.044, .049]	279.265*	11	-.021	-.019	+.004
Partial Strong	1122.354*	301	.919	.913	.043	[.040, .045]	72.643*	10	-.006	-.003	+.001
Strict	1331.116*	314	.900	.896	.047	[.044, .049]	152.833*	13	-.019	-.017	+.004
Partial Strict	1144.983*	313	.918	.915	.042	[.040, .045]	30.828*	12	-.001	+.002	-.001
Latent Variance-Covariance	1149.734*	316	.918	.916	.042	[.039, .045]	7.696	3	.000	+.001	.000
Latent Means	1172.395*	318	.916	.914	.042	[.040, .045]	20.166*	2	-.002	-.002	.000
Time-Invariant Measurement Models											
Perceived parenting	142.187*	26	.975	.957	.058	[.049, .067]	—	—	—	—	—
Latent Curve Models											
Unconditional	16.867*	1	.985	.956	.097	[.060, .140]	—	—	—	—	—
Predictors (freely estimated)	219.939*	28	.967	.936	.063	[.056, .071]	—	—	—	—	—
Predictors (equilibrium)	239.006*	32	.965	.940	.061	[.054, .069]	22.054*	4	-.002	+.004	-.002
Outcomes	20.072*	7	.997	.985	.033	[.017, .050]	—	—	—	—	—

Note. $*p < .05$; χ^2: robust chi-square test of exact fit; df: degrees of freedom; CFI: comparative fit index; TLI: Tucker–Lewis index; RMSEA: root mean square error of approximation; 90% CI: 90% confidence interval of the RMSEA; $\Delta\chi^2$ = robust (Satorra–Bentler) chi-square difference test (calculated from loglikelihood for greater precision); Δ: change in fit information relative to the previous model; ETEC: essentially tau-equivalent constraints.

Table 2

Parameter Estimates from the Unconditional Latent Curve Models

	Problematic Internet Use		
Growth parameters	Intercept factor	Linear slope factor	
Mean	3.675 (.033)**	-.038 (.008)**	
Variance	.827 (.032)**	.038 (.005)**	
Correlations between the Intercept and Slope factor	-.465 (.046)**		
	Time 1	Time 2	Time 3
Time-specific residuals	.331 (.021)**	.132 (.012)**	0 (.000)**

Note. **p* < .05; ***p* < .01; Numbers in parentheses are standard errors.

Table 3

Parameter Estimates from the Conditional Latent Curve Models

Predictor	Outcome	*b*	SE	β
Sex	PIU Intercept	.198**	.053	.105**
Paternal Care	PIU Intercept	.050	.051	.053
Maternal Care	PIU Intercept	-.100*	.045	-.106*
Paternal Neglect	PIU Intercept	.123*	.052	.126*
Maternal Neglect	PIU Intercept	-.024	.049	-.024
Academic Achievement Time 1	PIU Intercept	-.006	.024	-.006
Depressive Symptoms Time 1	PIU Intercept	.212**	.039	.209**
Substance Use Time 1	PIU Intercept	.038	.030	.037
Sex	PIU Slope	-.008	.014	-.020
Paternal Care	PIU Slope	-.004	.013	-.022
Maternal Care	PIU Slope	.018	.016	.093
Paternal Neglect	PIU Slope	-.022	.014	-.109
Maternal Neglect	PIU Slope	.005	.014	.025
Academic Achievement Time 1	PIU Slope	.005	.005	.026
Depressive Symptoms Time 1	PIU Slope	-.037**	.010	-.181**
Substance Use Time 1	PIU Slope	.001	.008	.006
Loneliness Time 1	PIU Time 2	.097**	.021	.091**
Loneliness Time 2	PIU Time 3	.097**	.021	.091**
PIU Intercept	Changes in Academic Achievement	-.088**	.033	-.068**
PIU Slope	Changes in Academic Achievement	-.240**	.089	-.062**
PIU Intercept	Changes in Depressive symptoms	-.073**	.021	-.103**
PIU Slope	Changes in Depressive symptoms	.308**	.080	.145**
PIU Intercept	Changes in Substance Use	.020**	.008	.081*
PIU Slope	Changes in Substance Use	-.005	.024	-.006

Note. **p* < .05; ***p* < .01; b: Unstandardized regression coefficients; SE: Standard errors of the coefficient; β = Standardized regression coefficients; PIU: Problematic internet use. Sex was coded as 0 = female, 1 = male.

Online Supplements for:

Longitudinal Trajectories, Social Antecedents, and Outcomes of Problematic Internet Use among Late Adolescents

These online supplements are to be posted on the journal website and hot-linked to the manuscript. If the journal does not offer this possibility, these materials can alternatively be posted on one of our personal websites (we will adjust the in-text reference upon acceptance).

We would also be happy to have some of these materials brought back into the main manuscript, or included as published appendices if you deem it useful. We developed these materials to provide additional technical information and to keep the main manuscript from becoming needlessly long.

Appendix 1: Specification of the Latent Change Model

Longitudinal latent change analyses were realized to assess how PIU trajectories were related to changes in depression, substance use, and academic achievement. To this end, three latent change models (e.g., McArdle, 2009) were estimated using Mplus 8 robust maximum likelihood estimator (MLR; Muthén & Muthén, 2017) and directly incorporated into the unconditional latent curve model. Latent change models made it possible to disaggregate the repeated measures of participants levels depression, substance use, and academic achievement into their initial levels (the Time 1 scores) and a latent change factor representing decline or growth occurring between Time 1 and Time 3. Latent change models for each variable were specified by (i) regressing the Time 3 score on the Time 1 score and fixing this regression path to be exactly 1; (ii) estimating a latent change factor defined on the basis of the Time 3 score (with the factor loading fixed to be exactly 1); (iii) fixing the intercept and residual of the Time 3 score to be exactly zero in order to freely estimate the mean and variance of the latent change factor; (iv) allowing the initial level to correlate with the latent change factor.

Table S1

Standardized Parameter Estimates for the Confirmatory Factor Analytic Model of Problematic Internet Use (Latent Mean Invariance)

	λ	δ
Item 1	.666**	.556
Item 2	.837**	.299
Item 3	.719**	.483
Item 4	.753**	.432
Item 5	.510**	.740
ω	.829	

Note. *p < .05; **p < .01; λ: standardized factor loadings; δ: item uniqueness; ω: McDonald's (1970) omega coefficient.

Table S2

Standardized Parameter Estimates for the Confirmatory Factor Analytic Model of Loneliness (Latent Mean Invariance)

	λ	δ
Item 1	.467**	.782
Item 2	.645**	.584
Item 3	-.324**	.895
Item 4	.772**	.404
Item 5	.739**	.453
Item 6	-.449**	.798
Item 7	.776**	.398
Item 8	.777**	.396
ω	.839	

Note. *p < .05; **p < .01; λ: standardized factor loadings; δ: item uniqueness; ω: McDonald's (1970) omega coefficient.

Table S3

Standardized Parameter Estimates for the Confirmatory Factor Analytic Model (with ETEC) of Perceived Parenting Practices

	Paternal care (λ)	Paternal overprotection (λ)	Maternal care (λ)	Maternal overprotection (λ)	δ
Item 1	.783**				.387
Item 2	.916**				.161
Item 3	.802**				.358
Item 4		.795**			.366
Item 5		.893**			.202
Item 6			.773**		.404
Item 7			.932**		.131
Item 8			.733**		.465
Item 9				.774**	.399
Item 10				.876**	.233
ω	.873	.834	.856	.812	

Note. *p < .05; **p < .01; ETEC: essentially tau-equivalent constraints; λ: standardized factor loadings; δ: item uniqueness; ω: McDonald's (1970) omega coefficient.

Table S4

Standardized Parameter Estimates for the Confirmatory Factor Analytic Model of the Outcomes (Latent Mean Invariance)

	Depressive symptoms (λ)	Substance use (λ)	δ
Item 1	.408**		.834
Item 2	.767**		.412
Item 3	.616**		.621
Item 4	.652**		.575
Item 5	.699**		.511
Item 6	.689**		.526
Item 7	.809**		.346
Item 8	.804**		.353
Item 9	.787**		.381
Item 10	.788**		.379
Item 11		.816**	.334
Item 12		.667**	.555
Item 13		.578**	.666/.846
ω	.909	.732/.710	

Note. **p* < .05; ***p* < .01; λ: standardized factor loadings; δ: item uniqueness; ω: McDonald's (1970) omega coefficient.

Table S5

Correlations for the Variables Used in this Study

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. PIU T1	—															
2. PIU T2	.730**	—														
3. PIU T3	.713**	.913**	—													
4. Loneliness T1	.258**	.237**	.229**	—												
5. Loneliness T2	.255**	.257**	.261**	.837**	—											
6. Loneliness T3	.223**	.238**	.279**	.788**	.861**	—										
7. Paternal care T1	-.086**	-.122**	-.100**	-.282**	-.259**	-.254**	—									
8. Paternal neglect T1	.166**	.150**	.148**	.280**	.241**	.240**	-.569**	—								
9. Maternal care T1	-.153**	-.148**	-.142**	-.222**	-.215**	-.212**	.541**	-.381**	—							
10. Maternal neglect T1	.154**	.127**	.134**	.247**	.228**	.223**	-.395**	.678**	-.567**	—						
11. Gender T1	.064**	.029	.054*	-.152**	-.145**	-.140**	.128**	-.047	.049	-.021	—					
12. Depressive symptoms T1	.226**	.203**	.207**	.621**	.531**	.497**	-.309**	.277**	-.289**	.251**	-.231**	—				
13. Depressive symptoms T3	.151**	.167**	.230**	.471**	.490**	.616**	-.235**	.194**	-.241**	.184**	-.212**	.693**	—			
14. Substance use T1	.074**	.085**	.079**	-.002	-.020	-.033	-.116**	.098**	-.138**	.118**	.010	.191**	.100**	—		
15. Substance use T3	.098**	.116**	.106**	.067*	.044	.029	-.160**	.126**	-.170**	.132**	-.019	.300**	.191**	.965**	—	
16. GPA T1	-.045	-.010	-.011	.047	.022	.046	.032	-.053	.046	-.042	-.066*	-.024	.012	-.095**	-.100**	—
17. GPA T3	-.069*	-.107**	-.117**	.051	.050	.042	.094**	-.045	.093**	-.069*	-.190**	-.054	-.037	-.159**	-.166**	.297**

Note. *p < .05; **p < .01; PIU: problematic internet use; GPA: grade point average; T1-T3: Time 1-Time 3. Gender was coded as 0 = male, 1 = female.

Table S6

Analyses of Variance Tests at Baseline based on the Number of Missing Time Points

Variable	F-value	p-value
Problematic Internet Use	.058	.943
Loneliness	3.263	.039
Paternal care	2.057	.128
Paternal neglect	1.761	.172
Maternal care	4.221	.015
Maternal neglect	2.004	.135
Depression	4.490	.011
Substance use	22.360	< .001
Academic achievement	23.300	< .001